Series Editors' Foreword

The topics of control engineering and signal processing continue to flourish and develop. In common with general scientific investigation, new ideas, concepts and interpretations emerge quite spontaneously and these are then discussed, used, discarded or subsumed into the prevailing subject paradigm. Sometimes these innovative concepts coalesce into a new sub-discipline within the broad subject tapestry of control and signal processing. This preliminary battle between old and new usually takes place at conferences, through the Internet and in the journals of the discipline. After a little more maturity has been acquired by the new concepts then archival publication as a scientific or engineering monograph may occur.

A new concept in control and signal processing is known to have arrived when sufficient material has evolved for the topic to be taught as a specialised tutorial workshop or as a course to undergraduate, graduate or industrial engineers. *Advanced Textbooks in Control and Signal Processing* are designed as a vehicle for the systematic presentation of course material for both popular and innovative topics in the discipline. It is hoped that prospective authors will welcome the opportunity to publish a structured and systematic presentation of some of the newer emerging control and signal processing technologies in the textbook series.

Methods adopted for use in industrial and process control systems are invariably straightforward in structure and easily implemented. The success of industrial PID controllers is often claimed to be due to these factors. The self-tuning controller is a technology, which has all the benefits of structural simplicity and is not very difficult to implement but has not been widely applied in industrial application. One possible reason is the recent extensive development of the robust controller paradigm where the "one size fits all" fixed controller philosophy reigns supreme. Of course, a conservative controller may come with a performance cost degradation so it is always useful to have several tools available for each controller task. And as Professor Bobál and his colleagues Professors Böhm, Fessl and Macháček show in this advanced course textbook the self-tuning controller can be very effective in preserving controller performance in the presence of slowly varying processes, and unknown process disturbances.

Advances on the industrial PID controller will not make the transfer to industrial practice unless there are lucid and direct textbooks available to aid engineers in understanding the potential of these techniques. In this textbook, Professor Bobál and his colleagues have captured their experiences in designing and applying the self-tuning controller method. The book gives a staged presentation that should enable the industrial engineer to develop new industrial applications of this adaptive control technique.

The context of self-tuning controllers is established in the opening three chapters of the book. In these chapters can be found a classification of adaptive control methods establishing the general position of the self-tuning controller method. Chapter 3 serves as an introduction to process model nomenclature and to the techniques of process identification to be used in the text.

Three thorough chapters then follow on different types of control design methods to be used in the self-tuning controller framework. These chapters examine closely the self-tuning PID controller (Chapter 4), the algebraic methods for self-tuning controller design like deadbeat, and pole-placement (Chapter 5) and finally, a self-tuning LQ controller (Chapter 6). Each chapter contains invaluable simulation examples and tips for tuning and implementing the various controller types.

The final two chapters deal with SIMULINK® simulation tools for gaining experience using the self-tuning controllers devised and recount the author team's experiences with some practical process applications. The highlight here is the application of an adaptive LQ controller to a heat-exchanger process.

Since the 1960s, the academic control community has devised many innovative controller methodologies but too few of them have made the transition to regular or widespread industrial practice. This new course textbook on the self-tuning controller method should enable industrial control engineers to gain an insight into the applications potential of this very transparent control technique. The material of the text also gives a good summary of both the theoretical and applications status of the method, which could prove valuable for graduate classes and for re-igniting the method as a research theme.

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Preface

The field of adaptive control has undergone significant development in recent years. The aim of this approach is to solve the problem of controller design, for instance where the characteristics of the process to be controlled are not sufficiently known or change over time. Several approaches to solving this problem have arisen. One showing great potential and success is the so-called self-tuning controller (STC).

The basic philosophy behind STCs is the recursive identification of the best model for the controlled process and the subsequent synthesis of the controller. A number of academics from universities and other institutes have worked intensively on this approach to adaptive control; K. J. Åström (Department of Automatic Control, Lund Institute of Technology), D. W. Clarke (Department of Engineering Science, University of Oxford), P. A. Wellstead (Institute of Science and Technology, University of Manchester), R. Isermann (Department of Control Engineering, Technical University of Darmstadt), I. D. Landau (Institut National Polytechnique de Grenoble), H. Unbehauen (Control Engineering Laboratory, Ruhr University Bochum) and also V. Peterka (Institute of Information Theory and Automation, Academy of Sciences of the Czech Republic, Prague) can be considered as pioneers in this field.

Although during research much effort has been devoted to meeting specific practical requirements it cannot be said that the above approach has been widely applied. On the other hand, many projects have been successfully put into practice. The characteristic common to all these projects was that there was a sufficiently qualified operator available who was both well acquainted with the technology in the field and able to take on board the scientific aspects of the work.

At this current stage of development in adaptive controllers there is a slight growth of interest in both the simpler and more sophisticated types of controller, particularly among universities and companies that deal with control design. It can be seen, however, that the lack of suitable literature in this field imposes a barrier to those who might otherwise be interested. We are referring especially to literature which can be read by the widest possible audience, where the theoretical aspects of the problem are relegated to the background and the main text is devoted to practical issues and helping to solve real problems. In comparison with the most recent publications on this subject, this book leans towards practical aspects, aiming to exploit the wide and unique experience of the authors. An important part of this publication is the detailed documentary and experimental material used to underline the elements in the design approach using characteristics in the field of time or frequency, dealing with typical problems and principles which guide the introduction of individual methods into practice. We should like to note that all the suggested control algorithms have been tested under laboratory conditions in controlling real processes in real time and some have also been used under semi-industrial conditions.

The book is organized in the following way. Chapter 1 gives a brief view of the historical evolution of adaptive control systems. The reader is introduced to problems of adaptive control and is acquainted with a classification of adaptive control systems in Chapter 2. Modelling and process identification for use in self-tuning controllers is the content of Chapter 3. Chapter 4 discusses self-tuning PID (Proportional-Integral-Derivative) controllers. Algebraic methods used for adaptive controller design are described in Chapter 5. Chapter 6 is dedicated to controller synthesis based on the minimization of the linear quadratic (LQ) criterion. Toolboxes have been created for the Matlab®/Simulink® programming system. They serve to demonstrate designed controller properties and help in applications of controllers in user-specific cases. They are described in Chapter 7. Chapter 8 is devoted to practical and application problems. This chapter is based on the rich practical experience of the authors with implementation of self-tuning controllers in real-time conditions.

Although this book is the product of four workplaces (two universities, academia and industry), the authors have tried to take a unified approach. Of course, this has not always been possible. The original work is followed by a list of literature treating the problem under discussion. We assume the reader knows mathematics to technical university level.

This book was created by a team of authors. Chapter 2 was written by V. Bobál, Chapter 3 by V. Bobál together with J. Böhm. V. Bobál and J. Fessl created Chapter 4 as follows: Sections 4.1 and 4.2 they wrote together, Sections 4.3, 4.4, and 4.5 are by J. Fessl, and Sections 4.6, 4.7, 4.8, and 4.9 are by V. Bobál. J. Macháček and V. Bobál wrote Chapter 5. Chapter 6 was written by J. Böhm and Chapter 7 by V. Bobál and J. Böhm. Finally Chapter 8 is a corporate work by all authors.

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We would finally like to thank the Series Editors Professor M. J. Grimble and Professor M. A. Johnson for their support during the publication of this book.

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2

Adaptive Control Systems

The majority of processes met in industrial practice have stochastic character. Traditional controllers with fixed parameters are often unsuited to such processes because their parameters change. Parameter changes are caused by changes in the manufacturing process, in the nature of the input materials, fuel, machinery use (wear) *etc.* Fixed controllers cannot deal with this.

One possible alternative for improving the quality of control for such processes is the use of adaptive control systems, which has been made possible by the development of modern digital automation based on microprocessor technology. Naturally this must be taken together with the development and improvement of adaptive control algorithms, and the exploration of their potential, advantages and limitations.

This chapter is divided into two main sections followed by a summary in Section 2.3. Formulation of the adaptive control problem is introduced in Section 2.1, and classification of adaptive control systems from the point of view of basic approach in Section 2.2.

2.1 Formulation of Adaptive Control Problem

Originally, adaptation was displayed only by plants and animals, where it is seen in its most varied forms. It is a characteristic of living organisms that they adapt their behaviour to their environment even where this is harsh.

Each adaptation involves a certain loss for the organism, whether it is material, energy or information. After repeated adaptations to the same changes, plants and animals manage to keep such losses to a minimum. Repeated adaptation is, in fact, an accumulation of experiences that the organism can evaluate to minimize the losses involved in adaptation. We call this learning.

Alongside such systems found in nature there are also technical systems capable of adaptation. These vary greatly in nature, and a wide range of mathematical tools are used to describe them. It is therefore impossible to find a single mathematical process to define all adaptive systems. For the purposes of our definition of adaptive systems we will limit ourselves to cybernetic systems which meet the following assumptions:

- their state or structure may change;
- we may influence the state or output of the system.

One possible generalized definition of an adaptive system is as follows:

The adaptive system has three inputs and one output (Figure 2.1). The environment acting on the adaptive system is composed of two elements: the reference variable w and disturbance v. The reference variable is created by the user but, as a rule, the disturbance cannot be measured. The system receives information on the required behaviour Ω, the system output is the behaviour of the system (decided rule)

$$y = f(w, v, \boldsymbol{\Theta}) \tag{2.1}$$

which assigns the single output y to each behaviour occurring in environments w and v. A change in behaviour, *i.e.* a change in this functionality, is effected by changing parameters $\boldsymbol{\Theta}$. For each combination $(w, v, \boldsymbol{\Theta})$ we select in place of $\boldsymbol{\Theta}$ parameter $\boldsymbol{\Theta}^*$ so as to minimize loss function g (for unit time or for a given time period)

$$g(\Omega, w, v, \boldsymbol{\Theta}^*) = \min g(\Omega, w, v, \boldsymbol{\Theta}) \tag{2.2}$$

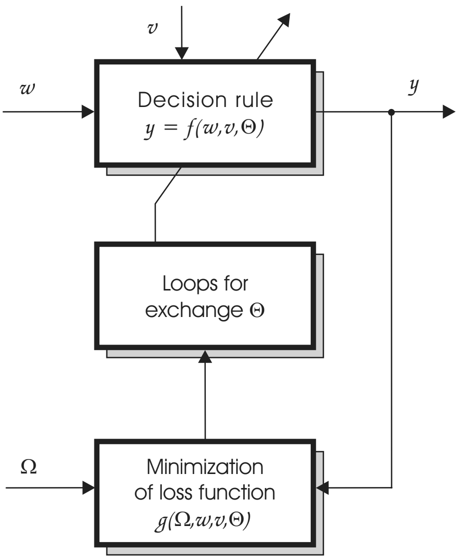

Figure 2.1. Inner structure of an adaptive system

In this case adaptation is the process used to search for $\mathbf{\Theta}^*$ and continues until this parameter is found. A characteristic property of an adaptive system is the fact that the process of adaptation always occurs when there is a change in the environment w or v or a change in the required behaviour Ω. If a change occurs after each time interval T_0 adaptation will take place repeatedly at the start of each interval. If the adaptation then lasts for time τ (after which loss g decreases) then the mean loss will be lower with a smaller ratio τ/T_0. The inverse value of the mean loss is known as the adaptation effect.

We mention here the so-called learning system. The learning system can be seen as a system that remembers the optimal value of parameter $\mathbf{\Theta}^*$ on finishing the adaptation for the given m triplet (w_m, v_m, Ω_m) of sequence $\{(w_m, v_m, \Omega_m)\}$, for $k = 1, 2, \ldots, m, \ldots, \infty$, and uses it to create in its memory the following function

$$\mathbf{\Theta}^* = f(w, v, \Omega) \tag{2.3}$$

On completing the learning process the decided rule for every behaviour in environments w and v can be chosen directly by selecting the appropriate value for parameter $\mathbf{\Theta}^*$ from memory without adaptation.

We can conclude, therefore, that an adaptive system constantly repeats the adaptation process, even when the environment behaviour remains unchanged, and needs constant information on the required behaviour. A learning system evaluates repeated adaptations so as to remember any state previously encountered during adaptation and when this reoccurs in the environment, does not use Equation (2.2) to find the optimum but uses information already in its memory.

Adaptive and learning systems can be used to solve the following tasks:

- recursive identification – *i.e.* the creation of a mathematical description of the controlled process using self-adjusting models;
- the control of systems about which we know too little before starting up to predefine the structure and parameters of the control algorithm, and also systems whose transfer characteristics change during control;
- recognition of subjects or situations (scenes) and their classification. Adaptive and learning systems are then components of so-called classifiers;
- manipulation of subjects – *i.e.* change of their spatial position. Adaptive and learning systems are then components of robots.

Further we will focus only on problems of adaptive control. Figure 2.2 shows a general block diagram of an adaptive system. According to this diagram we can formulate the following definition:

An adaptive system measures particular features of the adjustable system behaviour using its inputs, states and outputs. By virtue of comparison of these measured features and sets of required features it modifies parameters and the structure of an adjustable loop or generates an auxiliary input so that the measured features track as closely as possible the required features.

This definition is fairly general and allows inclusion of most of the adaptive problems of technical cybernetics. Features of the behaviour can take different forms in these problems. If the adaptive system is used for control, the behaviour feature could be, for example,

- pole and zeros assignment of a closed loop system;
- the required overshoot of the step response of a closed loop system to reference and input disturbances;
- the settling time;
- the minimum value of various integral or summing criteria;
- the amplitude and natural frequency of oscillations in nonlinear loops;
- the frequency spectrum of a closed loop control system;
- the required value of gain and phase margins *etc.*

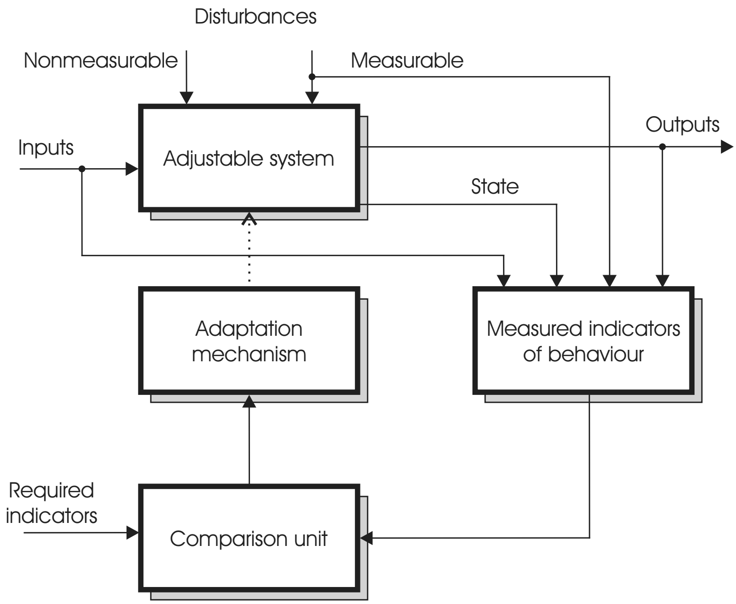

Figure 2.2. General block diagram of adaptive control system

For the purposes of automatic control we can simplify the definition of an adaptive system still further:

Adaptive control systems adapt the parameters or structure of one part of the system (the controller) to changes in the parameters or structure in another part of the system (the controlled system) in such a way that the entire system maintains optimal behaviour according to the given criteria, independent of any changes that might have occurred.

Adaptation to changes in the parameters or structure of the system can basically be performed in three ways:

- by making a suitable alteration to the adjustable parameters of the controller;
- by altering the structure of the controller;
- by generating a suitable auxiliary input signal (an adaptation by the input signal).

2.2 Classification of Adaptive Control Systems

The difference between classic feedback controllers and adaptive controllers is that the classic controller uses the principle of feedback to compensate for unknown disturbances and states in the process. Feedback is fixed and amplifies or otherwise modifies the error $e = w - y$ (w is the reference value of process output y), which in turn determines the value of the input signal u (controller output) for the system. The way in which the error is processed is the same in all situations. The basis of the adaptive system is that it alters the way in which the error is processed, *i.e.* adapts the control law to unknown conditions and extends the area of real situations in which high quality control can be achieved. Adaptation can be understood as feedback at a higher level where the controller parameters change according to the quality of the control process.

In recent years the theory of adaptive control has made significant developments. Obviously, as in any other new scientific discipline, the theory of adaptive control has no unified approach to classifying the systems operating on this principle. Here it suffices to use the classification set out in Figure 2.3; learning systems are not included. For detailed adaptive control systems classification according to different approaches see [7].

Adaptive systems based on the *heuristic approach*, *self-tuning controllers* (STC) and *model adaptive reference systems* (MRAS) are currently the three basic approaches to the problem of adaptive control. Adaptive systems which have a variable structure will purposely alter their structure following the set procedure. Since such a system alters its structure on the basis of experience gained previously in its working life, it may be regarded as a *self-organizing system.*

2.2.1 Adaptive Controllers Based on a Heuristic Approach

Methods using this approach provide adaptability directly either by evaluating the process output (or its error) or selected quality criteria for the control process. In these cases the algorithm for a PID digital controller is often used and we usually select the level of oscillation in the process output, or its error, as the criterion. These methods do not require identification of the controlled system. In some cases it is not even necessary to monitor the output error or introduce special test signals. A block illustration of these methods is given in Figure 2.4. Process output y, or error e, are evaluated according to the

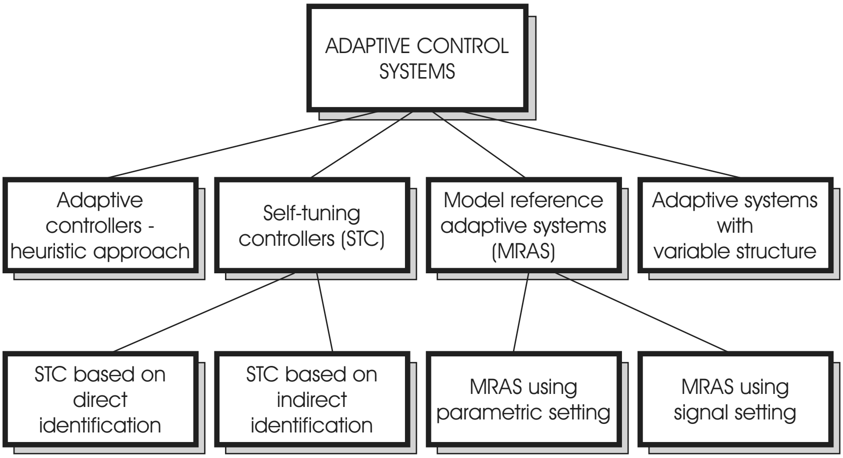

Figure 2.3. Classification of adaptive control systems

supplied criterion and subsequently preset the parameters of a PID controller.

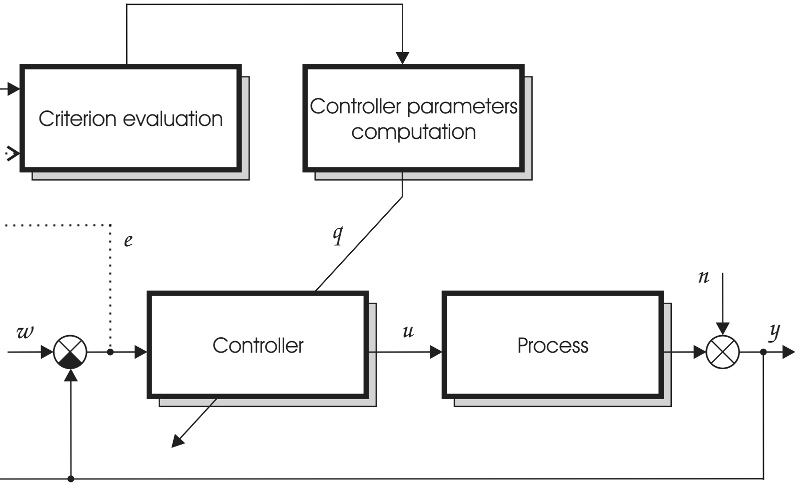

Figure 2.4. Diagram of the heuristic approach to adaptive control

When synthesizing this kind of controller we try to optimize the criterion that quantifies the quality of the control process. Although this approach satisfies practical applications while also being robust, it comes up against a number of calculation problems and has only been successfully applied in the simplest cases.

One of these successful applications is the approach designed by Maršík [8]; the method involves setting the gain of the PID controller and selecting the oscillation range as the directly measurable criterion. We know that the control process oscillates more as it approaches the limits of stability, while too damped a process ceases to oscillate at all. There are several modifications to this type of controller, some of which are so simple that they can even be realized by a few dozen fixed point operations.

Åström and Hägglund added the term self-tuning alongside the expression auto-tuning [9]. Although auto-tuning cannot be regarded as the same as self-tuning we will describe some of the principles of these controllers in this section. One example of this type of controller which has been fairly widely applied in practice is the auto-tuning controller designed by Åström and Hägglund [10, 11], where alongside the PID controller a relay type of nonlinearity is inserted in parallel into the feedback. During the adjustment phase the relay is introduced into the feedback causing the control loop to oscillate at a critical frequency. Since controller output u acquires only two values $\pm R$ and is therefore a rectangular process, the process output y has an approximately sine wave pattern, the shape of which depends on how the system filters harmonics out of the controller output. A simple Fourier series expansion of the relay output shows that the first harmonic component has amplitude $4R/\pi$. The ultimate (critical) gain K_{Pu} is then given as the ratio of the amplitude of the first harmonic component and the error amplitude $e_{\max}$

$$K_{Pu} = \frac{4R}{\pi e_{\max}} \tag{2.4}$$

The ultimate (critical) period T_u is measured from the cycling.

The controller can also be automatically adjusted by evaluating transient processes. Kraus and Myron [12] describe the so-called "EXACT Controller" (Expert Adaptive Controller Tuning) from the company Foxboro. This auto-tuning controller uses the pattern recognition approach, *i.e.* knowledge of the error process during transition. To make adjustments the controller uses three peaks from the error process to calculate overshoot and undershoot, which in turn is used together with the oscillation period to set the parameters for the PID controller. Some authors (such as Nishikawa *et al.* [13]) suggested adjusting PID controllers by measuring system response of the reference signal or process output in an open or closed loop. The parameters of the PID controller are optimized by calculating the integral linear or quadratic criterion for control process quality. In recent years much has been published on auto-tuning controllers, especially of the PID type (see [14, 15] and others).

2.2.2 Model Reference Adaptive Systems

The problem of model reference adaptive systems design is theoretically well elaborated and widely discussed in the scientific literature [16, 17]. The basic block diagram of the model reference adaptive system is shown in Figure 2.5.

The reference model gives requested response y_m or requested state vector x_m to reference input signal u_r.

This approach is based on observation of the difference between the output of the adjustable system y_s and the output of the reference model y_m.

The aim of the adaptation is convergence of the static and dynamic characteristics of the adjustable system, *i.e.* the closed loop, to the characteristics of the reference model. This, in fact, is an adaptive system with forced behaviour where the comparison between this forced behaviour and the behaviour (response) of the adjustable system (control loop) y_s, provides the error $\boldsymbol{\varepsilon}$. The task of the appropriate control mechanism is to reduce error $\boldsymbol{\varepsilon}$ or errors in the state vector x between the reference model and the adjustable system to a minimum for the given criteria. This is done either by adjusting the parameters of the adjustable system or by generating a suitable input signal, as can be seen in Figure 2.5.

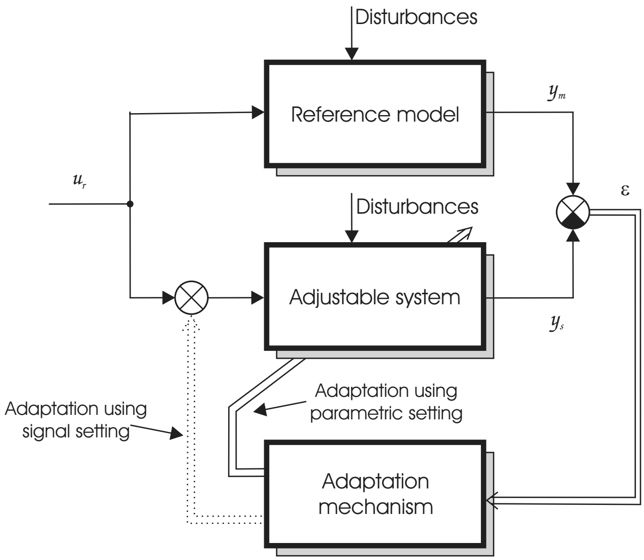

Figure 2.5. Basic block diagram of a model reference adaptive system

The dual character of this adaptive system is important since it can be used both for control and to identify the parameters of the model process or to estimate the state of the system. These systems are, to a certain extent, limited by the fact that they are only suited to deterministic control, however prospects for their wider use are good.

2.2.3 Self-tuning Controllers

For the two approaches previously outlined the design of an adaptive controller did not require detailed knowledge of the dynamic behaviour of the controlled system. Another approach to adaptive control is based on the recursive estimation of the characteristics of the system and disturbances and updating the estimates, so monitoring possible changes. Using this knowledge, appropriate methods can be employed to design the optimal controller. This kind of controller, which identifies unknown processes and then synthesizes control (adaptive control with recursive identification) is referred to in the literature as a self-tuning controller – STC. The most useful results in practical terms have been achieved mainly in one-dimensional systems for which a number of numerically stable algorithms of varying complexity have been designed. These algorithms can then be applied via a control computer equipped with a unit to interface with the technological environment. Expanding this to multivariable systems in many cases does not cause fundamental problems.

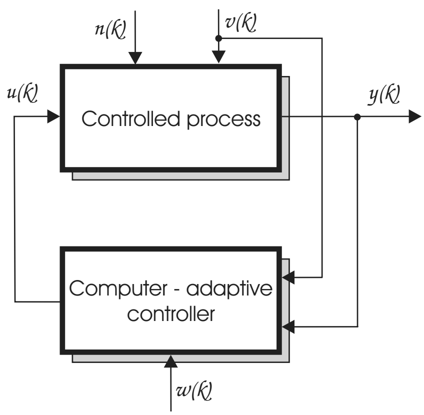

Figure 2.6. Basic block diagram of digital adaptive control loop

We assume a controlled technological process with a single process input $u(k)$ and a single process output $y(k)$. In addition, measurable disturbance $v(k)$ and nonmeasurable disturbance $n(k)$ – random noise – may affect the controlled process. A computer working as the digital adaptive controller is connected in feedback to the controlled process and, among other things, processes the required value of the process output. The block diagram of this basic feedback loop is given in Figure 2.6.

An adaptive digital controller works with a fixed sampling period T_0. A controller with this period generates a sequence of numerical values for the controller output $\{u(k); k = 1, 2, \ldots\}$ (assuming $T_0 = 1$). The discrete controller output $u(k)$ operates via an digital–to–analogue (D/A) converter and actuator in the closed loop. The controller output value is constant during the sampling interval. The actuator, including D/A converter, is included in the dynamics of the controlled process. The output of the controlled process is a physical (usually continuous-time) variable, which is also sampled over period T_0. Therefore, as far as the controller is concerned, the process output is a sequence of numerical values $\{y(k); k = 1, 2, \ldots\}$ and this is the only information the controller has regarding the continuous-time output. It can sometimes be useful to filter the continuous-time system output before sampling. The sensor, A/D converter and any filter being used are also regarded as part of the controlled process.

The basic feedback loop can be extended by a forward loop from the externally measured disturbance $v(k)$, if such measurements are available. Its behaviour is also sampled over period T_0 and transferred to the controller as a sequence of numerical values $\{v(k); k = 1, 2, \ldots\}$, and at the same time the reference variable value is digitally expressed as a sequence of numerical values $\{w(k); k = 1, 2, \ldots\}$. The existence of random nonmeasurable disturbance $v(k)$ and any change in the reference variable value $w(k)$ is the reason for introducing automatic control. The aim of control is to compensate these disturbances as well as to track the reference variable values. Further, we assume that the parameters of the controlled process are either constant but unknown or variable, in which case changes in these parameters are significantly slower than the speed of the adaptation process. Depending on the nature of the controlled process we can see how the following aims can be achieved using adaptive control with recursive identification:

- automatic tuning of the digital controller;
- improved control where nonstationary disturbances are present;
- the detection of changes in the parameters of the controlled system arising from various technological causes, for example changing the operating mode of the equipment;
- improvement in the control procedure of a given process by making a suitable change to the parameters of the digital controller.

Algorithmic Structure of Self-tuning Controllers

It is clear that to reach these goals the identification of the static and dynamic characteristics of a given process plays an important role together with the optimal control strategy itself. From parameter estimation theory we know that the determination of parameters is always burdened by a degree of uncertainty – error. This uncertainty not only depends on the number of identified steps (*i.e.* on the amount of sampled data) and on the choice of structure for the mathematical model of the controlled process, but is also dependent on the behaviour of the controller output, the sampling period and the choice of filter for the controller and process outputs. This means that every realized change in a controller output except the required control effect, also excites

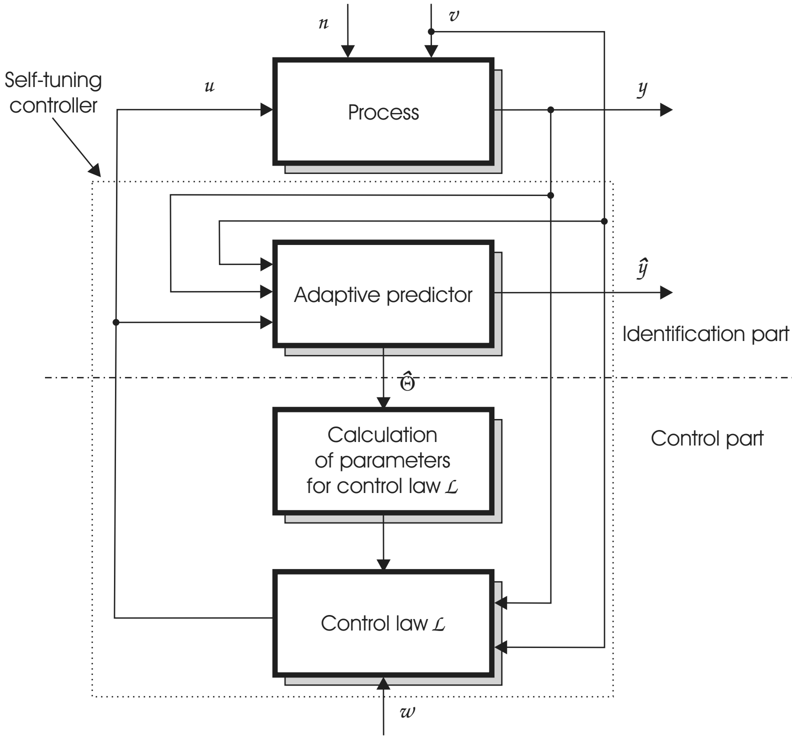

Figure 2.7. Internal algorithmic structure of a self-tuning controller

the controlled system and thus creates the conditions for its identification; in other words, for the best identification of the controlled process, it is necessary to impose certain conditions on the course of controller outputs.

The general task of optimal adaptive control with recursive identification is, therefore, extremely complicated because we have to seek within it a sequence of such controller outputs which can ensure that the mean process output value is as close as possible to the target value and at the same time enable the most accurate identification of the given process. Feldbaum [18] has presented a design for optimal control which, to a certain extent, fits the given assumptions. Because this design for optimal control has two effects it is called dual optimal control. Unfortunately, due to the complexity of the calculations it involves, dual optimal control is too demanding to be of use in most situations. Although exceptional efforts have been devoted to dual optimal control, not even the use of various simplified approximations has managed to reduce it to a stage where it can be applied practically.

It has, therefore, been necessary to simplify the solution to this problem using experimental experience and intuition. This solution is called forced separation of identification and control – the Certainty Equivalence Principle. The principle of this simplification is outlined in the following procedure:

1. The vector of process model parameters $\mathbf{\Theta}$ are regarded as being known for each control step and this equals its point estimate, which is available at any given moment, *i.e.* $\mathbf{\Theta} = \hat{\mathbf{\Theta}}(k-1)$.
2. The design of the control strategy to affect the desired control quality criteria is based on this assumption and the required controller output $u(k)$ is calculated.
3. Having acquired a new sample of process output $y(k)$ (or external measured disturbance $v(k)$) and known controller output $u(k)$ a further step in identification is performed using a recursive identification algorithm. This means that the new information on the process deduced from the three data items $\{u(k), y(k), v(k)\}$ is used to update estimate $\hat{\mathbf{\Theta}}(k-1)$ and the entire procedure is repeated to make a new estimate $\hat{\mathbf{\Theta}}(k)$.

From experience gained during experimentation we can see that the majority of practical tasks of adaptive control with recursive identification are suited to the given simplified approach.

The approach described above implies the inner algorithmic structure of the self-tuning controller schematically shown in Figure 2.7. The forced separation of identification and control splits the inner controller structure into parts for identification and control, which are only connected through the transfer of point parameter estimates $\hat{\mathbf{\Theta}}(k)$. Recursive estimation of the process model parameters is carried out in the identification part and used to predict value $\hat{y}(k)$ of process output $y(k)$. The control part contains a block to calculate the control parameters (control law L) using the process model parameter estimates $\hat{\mathbf{\Theta}}(k)$. The control parameters then serve to calculate the value of controller output $u(k)$ for each sampling period.

As can be seen from the structure above, reliable and quickly convergent identification is absolutely vital if the controller is to function well. Even though certain specific conditions are applied to the synthesis of adaptive control we can state that, where identification works well, synthesis can be carried out using known algorithms such as those for pole assignment design, dead-beat control, minimum variance control, generalized minimum variance control, linear quadratic control, and digital synthesis methods for PID controllers. The STC algorithms mentioned in this monograph differ only in the control path; for identification we will be using the recursive least squares method.

In some STCs the identification process does not serve to determine estimates of the process model parameters $\hat{\mathbf{\Theta}}(k)$, rather, appropriate reparametrization of the control loop can be used recursively to estimate the controller parameters directly. This means it is necessary to find the relationship between the process input and output and define it directly from the controller parameters without recalculating them using the estimates of the process model parameters. These controllers are referred to as being *implicit*,

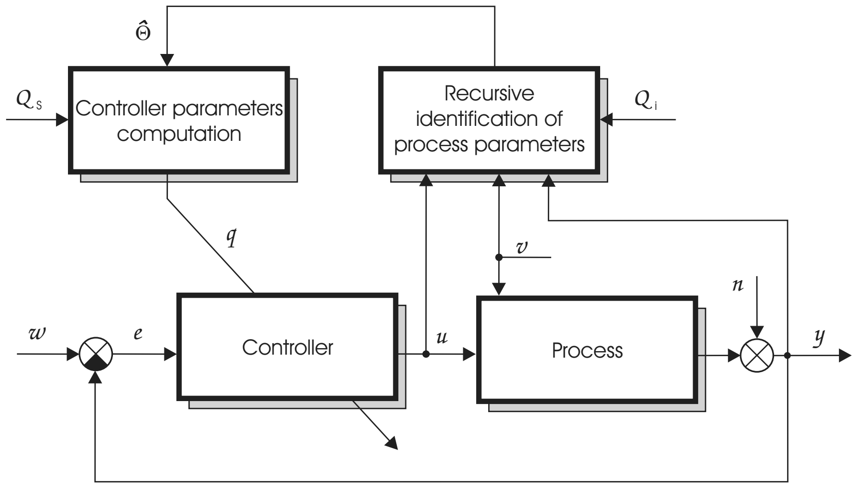

Figure 2.8. Block diagram of an explicit STC (with direct identification)

whereas controllers using a synthesis from estimates of the process model parameters are called *explicit*. If we illustrate an explicit STC using a diagram like the one in Figure 2.8, which is analogous to Figure 2.7, where Q_i is the identification criterion, Q_s the controller synthesis criterion and q are the controller parameters, we may draw a diagram of an implicit STC as in Figure 2.9.

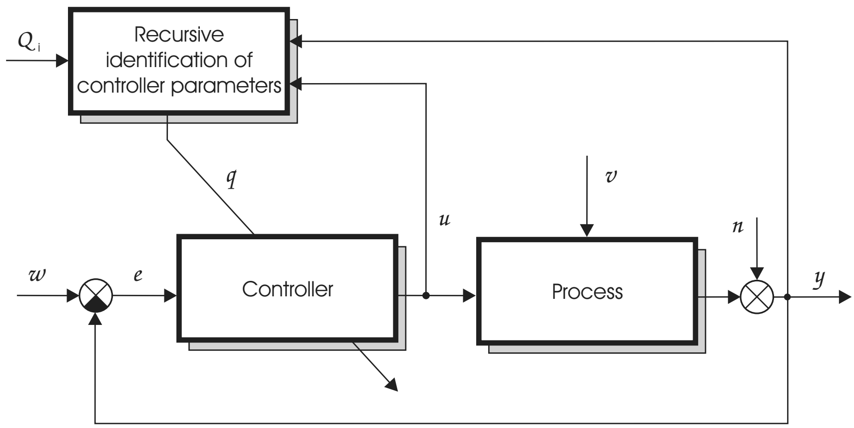

Figure 2.9. Block diagram of an implicit STC (with indirect identification)

The STC principle can also be used for one-shot controller tuning (autotuning). If the algorithm illustrated in Figure 2.7 is used for controller autotuning then the blocks representing recursive identification and controller parameter calculation are only connected at the moment when the controller is being set up, *i.e.* during the adjustment phase. Once the controller has been adjusted they are disconnected. The system is then controlled by fixed parameters. Clearly, this method of control is useful for deterministic processes where identification is switched off once the controller has been adjusted. The underlying principle of this type of controller is shown in Figure 2.10.

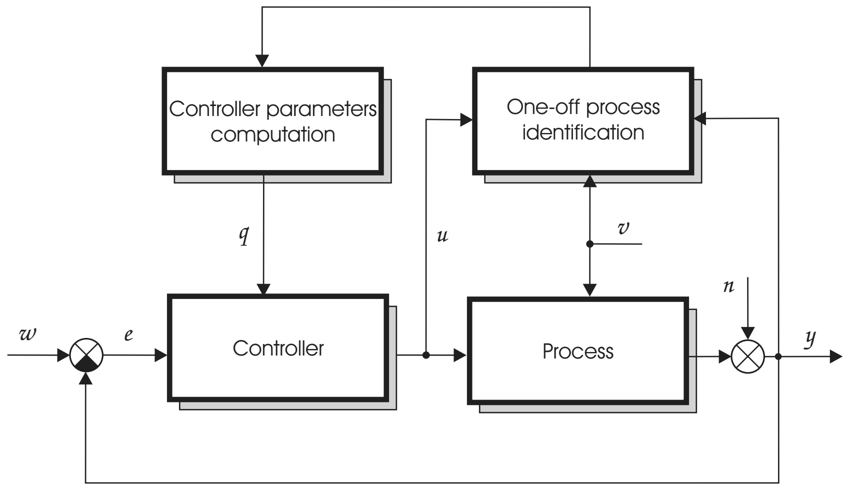

Figure 2.10. Block diagram of an auto-tuning controller using a one-off identification process

Development of Self-tuning Controllers

Here we give a brief history of the development of explicit STCs. The approach used in STCs was first mentioned in the work of Kalman [19] in 1958. He designed a single-purpose computer to identify the parameters of a linear model process and subsequently calculate the control law using minimum quadratic criteria. This problem was revived in the early 1970s by the work of Peterka [20] and Åström and Wittenmark [21] and others. The approach has been developed significantly since then. The first STCs were designed so as to minimize system output variance where some disadvantages were removed by the general minimization of output dispersion method developed by Clarke and Gawthrop [22, 23]. These are known as single-step methods because only one sample of the process output is considered in the quadratic criterion. One great disadvantage is that they are unable to control the so-called nonminimum phase systems, which are processes where the polynomial $B(z)$ (the polynomial which is included in the controlled system transfer function numerator) has its poles outside the unit circle of the complex z-plane, *i.e.* in an unstable area.

This problem can be solved by using multi-step criteria (to limit an infinite number of steps) which is a solution to the general quadratic problem. Peterka analyzed the probability rate of the Bayessian approach to adaptive control based on linear quadratic synthesis [24]. In general this control synthesis involves rather complex iteration calculations [25]. It has been shown that analytic methods may be used to find relatively simple explicit relationships to determine the optimal controller for one-dimensional models that are no higher than second order (see Böhm *et al.,* [26]).

In the late 1970s, early 1980s the first work was done on STCs based on pole assignment [27, 28]. During the 1980s much attention was also paid to single- and multi-step prediction adaptive methods [29, 30]. Hybrid STCs using a δ operator have similarly been analyzed [31]. Alongside these developments there has been exploration into synthesis methods for digital PID controllers which might be able to use parameter estimates gained through recursive identification to calculate controller intervention. These parameters are then used to calculate the PID controller elements, that is gain K_P, and integral and derivative time constants T_I and T_D [32, 33].

Problems for Further Research of Self-tuning Control Design

The principles of adaptive controllers bring also some drawbacks, mainly in the area of reliability, a property that is very important for any application. The problem is caused mainly by the identification part. Conditions for unbiased estimation cannot always be satisfied. Most of the present adaptive controllers consider only model parameter adaptation. Thus adaptive controllers are suitable only for slowly varying processes. In cases when parameter changes are abrupt, *e.g.* in the case of nonlinearities, fault states or rapid changes of process working conditions, parameter adaptivity cannot react properly.

To improve the identification part, developments in the following areas may be promising:

- use of different, usually more complex, identification methods which have less strict conditions for correct estimation;
- use a set of fixed models describing the given plant instead of on-line identification;
- use of a supervisor, monitoring controller behaviour and correcting its behaviour.

The idea of a supervisor deserves further attention. A supervisor can be implemented simply and some forms of it are now frequently used. Any practical application is completed by a process-specific supervisor that switches the adaptive controller over to an available standard controller in the case of unexpected controller behaviour.

A data-dependent forgetting factor in identification is now standard [34]. Data-dependent controller synthesis is used in Chapter 6 and Chapter 8.

More complex supervisors can be developed based on artificial inteligence approaches. Methods such as fuzzy logic, evolutionary algorithms [35, 36], or their combination show themselves to be promising methods from the artificial intelligence field [37, 38]. An intelligent supervisor based on these methods can be used. Its task generally is parameter adjusting and/or choice of an appropriate controller. If a fuzzy supervisor is used, then it can be regarded as a set of static nonlinear I/O functions. Its task is controller parameter adjustment if needed, and/or the choice of an appropriate controller from classes of controllers. Adjustment of the fuzzy controller must be done for error-free function. Today, there are three common methods for this. In the first, an expert adjusts all fuzzy logic properties according to his experience; in the second, some sophisticated method is used [39]; and finally in the third, a fuzzy supervisor is adjusted on-line by means of modern evolutionary algorithms [35]. If the evolutionary algorithm is used like an evolutionary supervisor, *i.e.* independently of other methods, then its entire task can be regarded as a nonlinear constrained multi-objective optimization problem. An advantage of such a supervisor is its simplicity, universality, and of course, its independence from a human operator. Nowadays, similar methods are applied in intelligent sensors for the class of so-called fault-detection tasks.

2.3 Summary of chapter

This chapter gives a formulation of the adaptive control problem, and defines those problems that can be solved using adaptive systems. A simplified definition of the adaptive system suitable for the design of adaptive control loops is also given. Adaptive control systems can be classified as adaptive controllers based on heuristic approach, model reference adaptive systems, and self-tuning controllers.

The principles of the self-tuning controller are described including its algorithmic structure. The differences between implicit and explicit versions of the self-tuning controller are also explained. The chapter concludes with a summary of the historical development of self-tuning controllers and describes further developments in this area of adaptive control.

Problems

2.1. Clarify the general term “adaptivity” and utilization of the principle for process control.

2.2. Describe a class of technological processes suitable for the implementation of adaptive controllers.

2.3. Design a block diagram of an MRAS for adaptive system identification.

2.4. What are the differences between explicit and implicit versions of STC?