Adaptation, Auto-Tuning and Smart Controls

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ADAPTATION, AUTO-TUNING AND SMART CONTROLS

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Abstract. This paper reviews some advances in adaptive control that have occured since CPCII. This includes theoretical development, auto-tuning and industrial use. The possibility to use a collection of different algorithms for estimation, control design and monitoring which are coordinated by an expert system is a new emerging concept which is beginning to be explored.

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1. INTRODUCTION

There have been significant advances in adaptive control after the CPCII which was held in January of 1981. Theory and algorithm have been improved. More important however is the emergence of several industrial products for industrial process control. Leeds and Northrup announced their Electromax V which is a single loop controller with a self-tuning option in 1981. The swedish Company ASEA announced their Novatune, which is a small DDC system with several adaptive modules, in 1982. Three adaptive controllers were announced in 1984. The British company Turnbull Controls introduced their TCS 6355 auto-tuning controller, which is a single loop regulator with adaptive and auto-tuning facilities. The swedish company NAF Controls announced their Autotuner which is based on a novel scheme to tune PID regulators. Foxboro announced the adaptive single loop regulator Exact. There are also several other adaptive controllers which have been announced or which are about to appear.

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Today there are several thousand loops under adaptive control. The practical experiences from their operation is naturally accumulating. A description of some experiences are given in the paper (Dumont, 1986).

The products are based on different concepts and different regulator structures. The demands on the user are also quite different both with respect to operational issues and in the effort required to understand how they work. Most products are based on the PID algorithm but there are a few that uses other types of algorithms. Some use the traditional approach to adaptive control based on recursive parameter estimation and automatic control design, but others are using nonconventional methods for estimation and control design. The Foxboro Exact uses an heuristic design method which mimics the tuning procedure used by an operator. The NAF Autotuner uses a novel method to determine the process dynamics based on relay oscillation.

Most adaptive schemes currently used can be characterized as local gradient algorithms. This means that given good initial values they will drive the system towards a very good performance. The effort required to obtain the initial values or the prior knowledge may be substantial. Several adaptive systems therefore have what is called a "pretune mode" which typically uses a pulse test to obtain the required prior knowledge. The autotuner is different because it requires very little prior knowledge. It also generates the test signals automatically. There is also a growing awareness of the need for safeguards to ensure that the adaptive regulators work well under all possible operating conditions.

The purpose of this paper is to look at some of the approaches to adaptive control their strengths and weaknesses. In doing so it is found that systems with very attractive properties can be obtained by combining several different approaches. An autotuner can be used to arrive at a simple control law in a robust way. The information gathered by the autotuner can also be used to derive the prior information required by more sophisticated adaptive schemes. We will thus arrive at a system which contains several different algorithms. To monitor their operation it is then useful to introduce algorithms which supervise the operation of the system and which can initiate switching between algorithms. It is clear that a system of this type will involve a substantial amount of

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heuristic logic. Expert system methodologies provide a systematic approach for dealing with this logic. The term expert control is therefore coined to describe systems of this type. Once the expert system approach is taken it is also possible to obtain control systems with learning functions.

The purpose of this paper is to pinpoint some of these interesting developments that have taken place. The paper is organized as follows. The auto-tuner which is a simple and robust way to design systems with "push button tuning" is described in Section 2. The technique can also be used as a pre-tune mode for more complicated adaptive regulators. Conventional adaptive control based on recursive parameter estimation and control design is discussed in Section 3. The focus of the presentation is on algorithmic development. Some advances in adaptive control theory are presented in Section 4. This includes stability, convergence, robustness and universal stabilizers. Practical aspects on implementation of auto-tuning and adaptive systems are presented in Section 5. This is based on some published material on the commercial products and on my own experience. The discussion clearly indicates that there is a considerable amount of heuristics in current implementations. This serves as a motivation for Section 6 where it is attempted to combine algorithms and heuristics in an organized fashion by merging the fields of automatic control and expert systems. Some speculations on the future development of the field are given in the conclusions.

2. AUTOTUNING

For a long time the efforts in adaptive control were concentrated to comparatively complicated control systems. Only moderate interest were given to adaptation of simple controllers of the PID type. My own interest in this field started around 1980 when trying to respond to questions like the one posed by Ray Ash at CPCII: "Why don't you just provide an ordinary PID regulator with a tuning button?" A novel approach which solves this problem will be discussed in this section. This approach was originally presented in Åström and Hägglund (1983, 1984 a,b,c) and in Hägglund and Åström (1985 a,b,c). The approach was motivated by a desire to develop a simple robust tuning scheme which requires very little prior information. The approach is based on a special technique for

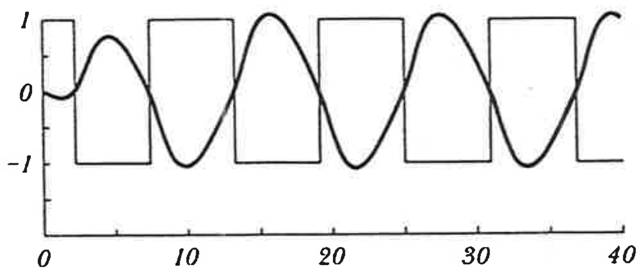

Fig. 1. Input and output signals for a system under relay feedback.

system identification which automatically generates an appropriate test signal and a variation of the the classical Ziegler-Nichols (1943) method for control design.

The Basic Idea

The Ziegler-Nichols method is based on the observation that the regulator parameters can be determined from knowledge of one point on the Nyquist curve of the open loop system. This point is the intersection of the Nyquist curve with the negative real axis. It is traditionally described in terms of the ultimate gain k_c and the ultimate period T_c. In the original scheme, described in Ziegler and Nichols (1943), the ultimate gain and period are determined in the following way: A proportional regulator is connected to the system. The gain is gradually increased until an oscillation is obtained. The gain k_c when this occurs is the critical gain and the oscillation has the critical period. It is difficult to perform this experiment automatically in such a way that the amplitude of the oscillation is kept under control.

The autotuner is based on the idea that the ultimate gain and the ultimate frequency can be determined by introducing relay feedback. A periodic oscillation is then obtained. The ultimate period T_c is simply the period of the oscillation and the critical gain can be determined from the relay amplitude and the amplitude of the oscillation, see Fig. 1.

If the process attenuates high frequencies so that the first harmonic component dominates the response it follows that the input and the output are out of phase. Furthermore if the relay amplitude is d it follows from a Fourier

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7. CONCLUSIONS

Control of systems with unknown parameters has been approached from two points of view automatic tuning and adaptive control. It has been demonstrated that both approaches lead to controllers which contain numerical algorithms as well as heuristic logic. The approaches are also complementary with respect to the prior information needed. It has been suggested to use an expert system to coordinate the different techniques and to add facilities like monitoring and tables for storing information about the process and its control system. The approach which clearly can be applied to a wide variety of problems seems to offer interesting possibilities to combine analytical and heuristic approaches. The incorporation of heuristics through AI structures results in systems that are far more flexible and transparent than selector and safety-jacket logic. Experience from building expert systems for real applications has shown that their power is most apparent when the problem considered is sufficiently complex. This paper has pointed out that an expert system can provide a framework for blending numerical algorithms with this detailed knowledge of dynamics and process control. This results in a feedback system with many interesting features which includes learning, store of increased process knowledge and explanatory power.

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series expansion that the first harmonic of the input is $4d/\pi$. If the amplitude of the output is a the process gain is thus $\pi a/4d$ and the ultimate gain becomes

$$k_c = \frac{4d}{\pi a} \tag{1}$$

Exact analyses of relay oscillations are also available. See Hamel (1949), Tsypkin (1958) and Åström and Hägglund (1984a). The period of an oscillation can be determined by measuring the times between zero-crossings. The amplitude may be determined from the peak-to-peak values of the output. These estimation methods are easy to implement because they are based on counting and comparison only. Simulations and extensive experiments on industrial processes have shown that the simple estimation method works well in comparison with the more sophisticated estimation methods. The simple methods also have some additional advantages, see Åström (1982).

Control Design

When the critical gain k_c and the critical period are known the parameters of a PID regulator can be determined by the Ziegler-Nichols rule which can be expressed as

$$k = \frac{k_c}{2} \qquad T_i = \frac{T_c}{2} \qquad T_d = \frac{T_c}{8} \tag{2}$$

This rule gives a closed loop system which is sometimes too poorly damped. There are therefore many modifications of the basic Ziegler Nichols rule.

A block diagram of a control system with auto-tuning is shown in Fig. 2. The system can operate in two modes. In the tuning mode a relay feedback is generated as was discussed above. When a stable limit cycle is established its amplitude and period are determined as described above and the system is then switched to the automatic control mode where a conventional PID control law is used.

The tuner is very easy to use. The process is simply brought to an equilibrium by setting a constant control signal in manual mode. The tuning is then activated by pushing the tuning switch. Simplicity is the major advantage of the auto-tuner. It is very easy for the operator to use it. It is also easy to

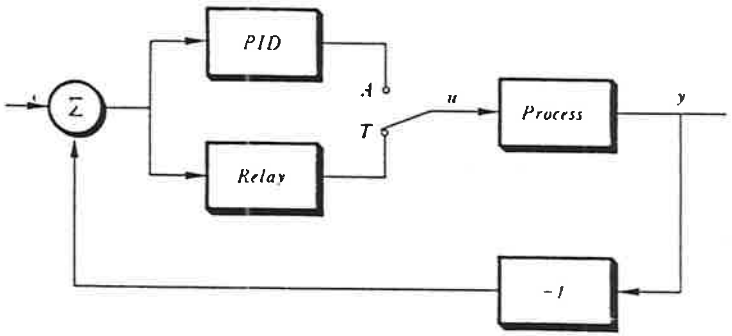

Fig. 2. Block diagram of an auto-tuner.
The system operates as a relay controller in the tuning mode (T) and as an ordinary PID regulator in the automatic control mode (A).

explain the auto-tuner to the instrument engineers. The properties of the autotuner are illustrated in Fig. 3, which shows an application to level control in three cascaded tanks. After bringing the system to an equilibrium the auto-tuner is initiated. The relay oscillation then appears. The amplitude measured in the first half-period indicates that the relay amplitude is too high. The relay amplitude is therefore reduced. When the oscillation has stabilized so that the amplitudes of two consequtive half periods are sufficiently close the critical gain and the critical period are determined and the regulator is switched to normal PID control. A set point change is later introduced manually. This shows that the tuning has resulted in a system with good transient behavior.

Prior Information

A major advantage of the autotuner is that it requires little prior information. Only two parameters the relay amplitude and the hysteresis width are required. In the NAF autotuner these parameters are set automatically. The relay amplitude is initially set to fixed proportion of the output range. The amplitude is adjusted after one half period to give an output oscillation of specified amplitude. The modified relay amplitude is stored for the next tuning. The hysteresis width is set automatically based on measurements of the measurement noise.

TABLE 1 Main Monitoring Table

An entry is made whenever there is a mode switch or a set-point change.

#	Time	u	σ_u	y	σ_y	Stable	Regulator type

Process data is stored in lists in the system data base. It is convenient to have event lists associated which each of the knowledge sources listed above. There will thus be a main monitoring table a minimum variance control table an auto-tuning table etc. A typical example of such a table is given in Table 1. An entry is made in this table when there is a major event in the system e.g. a set point change, a tuning, a switching of control modes etc.

It may be useful to add a few entries in the table such as max and min values or percentile values. From the data shown in Table 1 it is possible to make deductions like: What are the relations between the mean values of u and y? Do these relations change with time? Are there any relations between the standard deviations and the mean value of the control signal? What are the patterns of the mode switches? Does the system go to tuning mode after large set point changes? What control modes are used for most of the time? Are these drastic variations in performance with time and modes? The answers to these questions will allow us to make inference about the characteristics of the process.

A prototype system of the type outlined above has been implemented by Årzén using a VAX 11/780 running under VMS is used. The expert system is implemented in Lisp with the algorithms written in Pascal. Parallel processes are implemented using the VMS mail box facility. The expert system framework OPS4 is used. The design and some experiments are described in Årzén (1986).

DriftDetector

SelfTuning:
SelfTuningRegulation
SelfTuningSupervisor

Learning:
GetRegulatorParameters
SmoothAndStoreRegulatorParameters
TestSchedulingHypothesis

The following discussion explains some of the operators or actions that are used in the system. The "action" MinimumVarianceControl is a primary function of the regulator. The preconditions for this action include knowledge of an appropriate sampling period and models for the process and the disturbances. The process zeros are cancelled in minimum variance control. This may lead to ringing if the cancelled zeros are not sufficiently well damped. To detect ringing and to take the appropriate actions it is useful to include a RingingDetector. Ringing can be avoided by increasing the parameter d or by increasing the sampling period h, see Åström and Wittenmark (1985). There is a convenient way to find out if a process is under minimum variance control simply by calculating the autocorrelation of the process output, see Åström (1970). This can be used in the MinimumVarianceSupervisor.

If the process model required for minimum variance control is not available a self-tuning regulator may be used. This requires certain preconditions as was discussed in Section 3. If the prior information for a self-tuner is not available it can be attempted to use an auto-tuner, which requires less prior information. The data obtained from the auto-tuning experiment can be used to generate initial conditions for the self-tuner. The performance of a self-tuner depends critically on the process being properly excited. An ExcitationSupervisor can check this. If there is not enough excitation there are two options. Either to stop the updating or to introduce perturbation signals. using a PerturbationSignalGenerator. Other functions may also be provided. Assume that it is known that the process dynamics changes with a few parameters like production. Gainscheduling and learning may then be considered. This is done by storing control parameters for different operating conditions in tables.

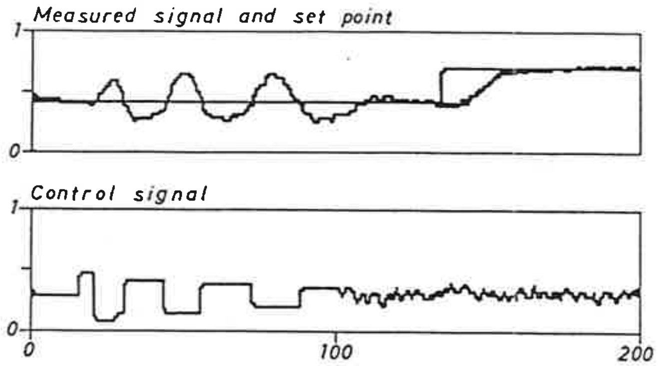

Fig. 3. Results obtained applying an auto-tuner to level control of three cascaded tanks.

Practical Aspects

There are several practical problems which must be solved in order to implement an auto-tuner. It is e.g. necessary to account for measurement noise, level adjustment, saturation of actuators and automatic adjustment of the amplitude of the oscillation. It may be advantageous to use other nonlinearities than the pure relay. A relay with hysteresis gives a system which is less sensitive to measurement noise. Measurement noise may give errors in detection of peaks and zero crossings. A hysteresis in the relay is a simple way to reduce the influence of measurement noise. Filtering is another possibility. The estimation schemes based on least squares and extended Kalman filtering can be made less sensitive to noise. Simple detection of peaks and zero crossings in combination with an hysteresis in the relay has worked very well in practice. See e.g. Åström (1982).

The process output may be far from the desired equilibrium condition when the regulator is switched on. In such cases it would be desirable to have the system reach its equilibrium automatically. For a process with finite low-frequency gain there is no guarantee that the desired steady state will be achieved with relay control unless the relay amplitude is sufficiently large. To guarantee that the output actually reaches the reference value, it may be necessary to introduce manual or automatic reset. It is also desirable to adjust the relay amplitude automatically. A reasonable approach is to require that the oscillation is a given percentage of the admissible swing in the output signal.

An Industrial Application

The concept of autotuning has been incorporated into a commercial regulator manufactured by NAF Controls in Sweden (Bååth and Hägglund, 1985). Figure 4 shows an application of this regulator to temperature control in a distillation column. The control loop considered had been behaving poorly for a long time. It was oscillating with the settings normally used ($K = 8$, $T_i = 2000$, and $T_d = 0$). At time 11.30 the regulator was switched to manual. Two hours later the output had settled reasonably well and the tuning was initiated at time 14.00. The logic for automatic selection of the noise limits and the relay amplitude took about an hour to settle. The measurement of the period and the amplitude of the oscillation started about time 15.00. The measurement was completed at time 20.00 and the regulator automatically switched to automatic control mode. Notice that the whole procedure was fully automatic from the time 14.00 when the tuning was initiated. Also notice that the severe disturbances at time 17.00 - 18.00 did not pose difficulties because of the robustness facilities built into the system. Finally observe the good performance of the regulator when the tuning was complete.

Extensions

There are several extensions of the simple auto-tuner. More information about the process characteristics can be extracted by analysing the waveform obtained under relay control. Improved design methods can also be obtained by measuring several points on the Nyquist curve. It is also easy to determine several points on the Nyquist curve by making relay feedback experiments with relays having modified characteristics. A relay with hysteresis has the describing function shown in Fig. 5A. A relay experiment with such a relay gives determines the intersection of the Nyquist curve with the describing function shown in Fig. 5A. The describing function can be translated vertically by changing the hysteresis width. By modifying the relay characteristics we can also obtain the characteristics shown in Fig. 5B. Several points can be

(1983b) it is shown that the logic for an auto-tuner is very conveniently implemented using an expert system.

An expert system has the interesting ability to explain its reasoning. This offers interesting possibilities for the control problem. We can thus get answers to questions like. What control law is beeing used? Why was this control law chosen? What is the current knowledge of the process and its environment? Are the fluctuations in the process output normal? The word 'expert control' has also been used in other contexts. Moore et al. (1984 a,b) have proposed to use the expert system in a supervisory mode as control advisors and alarm advisors. Other applications are given in Trankle and Markosian (1985) and Sanoff and Wellstead (1985).

An Example

The notion of expert control is illustrated by an example. Consider a simple regulation loop where the goal is to keep the process output close to a set point for a wide range of operating conditions. A list of the major operations in the system is given below.

```
MainMonitor:
    StabilitySupervisor
    ComputeMeansAndVariances
AutoTuning
    Tune
    KcTcEstimator
    DeterminePidStructure
    EstimateTimeDelay
BackUpControl:
    PidControl
    PidSupervisor
FixedGainMinimumVarianceControl:
    MinimumVarianceControl
    MinimumVarianceSupervisor
        RingingDetector
        DegreeSupervisor
Estimation:
    ParameterEstimation
    EstimationSupervisor
        ExcitationSupervisor
        PerturbationSignalGenerator
        JumpDetector
```

knowledge base. The other part is the runtime user interface. This contains explanation facilities that makes it possible to question how a certain fact was concluded, why a certain estimation algorithm is executing etc. It is also possible to trace the execution of the rules. The user interface wan also contain facilities to deal with natural language. Fancy graphics can also be helpful.

Planning

Expert control contains an element of planning. Consider for example the actions to be taken at ank on-line fault, or when it is desired to change operating conditions. The development of a suitable plan of actions may be viewed as a search through a large network to reach the desired goal. This searching and planning in a complex environment is a fundamental activity in AI systems.

Real Time Expert System

Expert systems normally interact via an operator who gives premises and goals. An interesting aspect of the expert control systems is that they can acquire knowledge automatically from the environment by injecting signals into a system and observing responses. Premises can also be generated automatically by signals from the sensors. It may take a long time to search through a large rule base. In an expert control system it may also happen that premises change with time. This poses significant problems.

Expert Control

The idea of expert control is to have a collection of algorithms for control, supervision and adaptation which are all supervised by an expert system. This offers several interesting possibilities. It was mentioned in Section 4 that heuristic logic is important for ordinary PID regulators and even more so for adaptive regulators. The logic shows up as if-then-else or case statements in the regulator code. In many cases the code for the logic is larger than the code for the control algorithm. The debugging, modification, and testing of the control logic can be very time consuming. An expert system is a very convenient way to implement this logic even if it is an overkill for PID control. In Åström

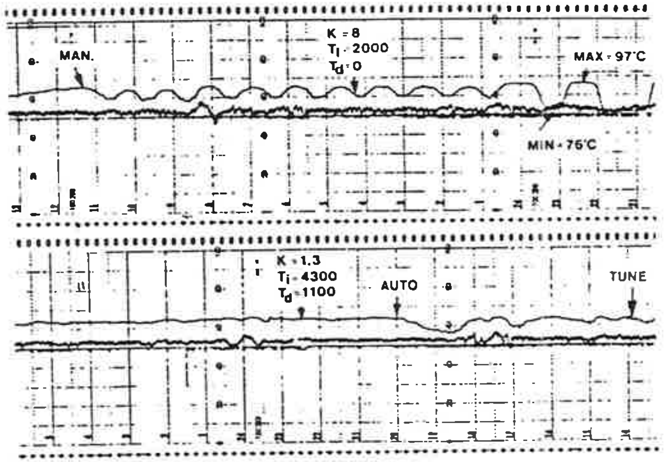

Fig. 4. Application of the auto-tuner to temperature control in a distillation column.

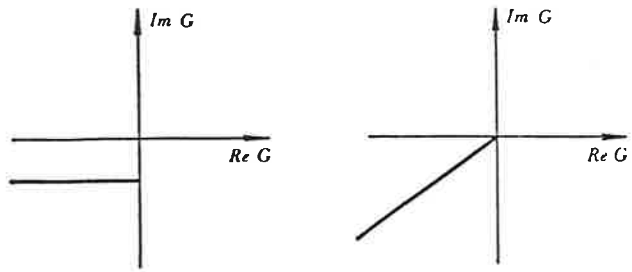

Fig. 5. Describing functions of relay with hysteresis and a relay with a modified hysteresis characteristics.

determined by changing the angle φ. Design techniques based on several points on the Nyquist curve are discussed in Åström and Hägglund (1984c), Hägglund and Åström (1985).

Auto-Tuning with Scheduling

Auto-tuning is a simple way to reduce uncertainty by experimentation. In many cases the characteristics of a process may depend on the operating conditions. If it is possible to measure some variable which correlates well with the changing process dynamics it is possible to obtain a system with interesting characteristics by combining the auto-tuner with a table look-up function. When the operating condition changes a new tuning is performed on demand from the operator. The resulting parameters are stored in a table together with the variable which characterizes the operating condition. When the process has been operated over a range covering the operating conditions the regulator parameters can be obtained from the table. A new tuning is then required only when other conditions change. A system of this type is semi-automatic because the decision to tune rests with the operator. The system will, however, continue to reduce the plant uncertainty.

3. ADAPTIVE CONTROL

A block-diagram of a conventional adaptive regulator is shown in Fig. 6. The adaptive regulator can be thought of as composed of two loops. The inner loop consists of the process and an ordinary linear feedback regulator. The parameters of the regulator are adjusted by the outer loop, which performs recursive parameter estimation and control design calculations. To obtain good estimates it may also be necessary to introduce perturbation signals. This function is not shown in Fig. 6 in order to keep the figure simple. Notice that the system may be viewed as automated modeling and design.

The block labeled "regulator design" in Fig. 6 represents an on-line solution to a design problem for a system with known parameters. This is called the underlying design problem. It is useful to consider this problem because it gives the characteristics of the system under the ideal conditions when the parameters are known exactly.

The adaptive regulator shown in Fig. 6 is very flexible. Both model reference adaptive system and self-tuning regulators can be represented by it. Many different design methods and many different parameter estimation schemes can be used. There are adaptive regulators based on phase- and amplitude margin design methods, pole-placement, minimum variance control, linear quadratic gaussian control and optimization methods. An interesting avenue which have not yet been pursued is to use robust design techniques which

database. The <conclusion> can result in a new fact being added to the data base or a modification of an existing fact. The <action> can be to activate an algorithm for diagnosis, control or estimation. These actions are different from those found in conventional expert systems. The rulebase is often structured in groups or knowledge sources that contain rules about the same subject. This simplifies the search.

In the control application the rules represent the skills about the control and estimation problem that we want to build into the system. This includes the appropriate characterization of the algorithms, judgemental knowledge on when to apply them and supervision and diagnosis of the system. The rules are introduced by the knowledge engineer via the knowledge acquisition system, which assists in writing and testing rules.

Inference Engine

The inference engine processes the rules to arrive at conclusions or to satisfy goals. It scans the rules according to a strategy which decides from the context (current data base of facts and goals) which production rules to select next. This can be done according to different strategies. In forward chaining it is attempted to find all conclusions from a given set of premises. This is typical for a data driven operation. In backward chaining the rules are traced backward from a given goal to see if it can be supported by the current premises. This is typical for a diagnosis problem. The search can be organized in many different ways depth first or breadth first. There are also strategies that use the complexity of the rules to decide the order in which they are searched. To devise efficient search procedures it is often convenient to decompose the rule base into pieces dealing with related chunks of knowledge. If the rules are organized in that way it is also possible for a system to focus its attention on a collection of rules in certain situations. This can make the search more efficient.

User Interface

The user interface of a production system can be divided into two parts. The first part is the development support that the system gives. This contains tools such as rule editor and rule browser for development of the system

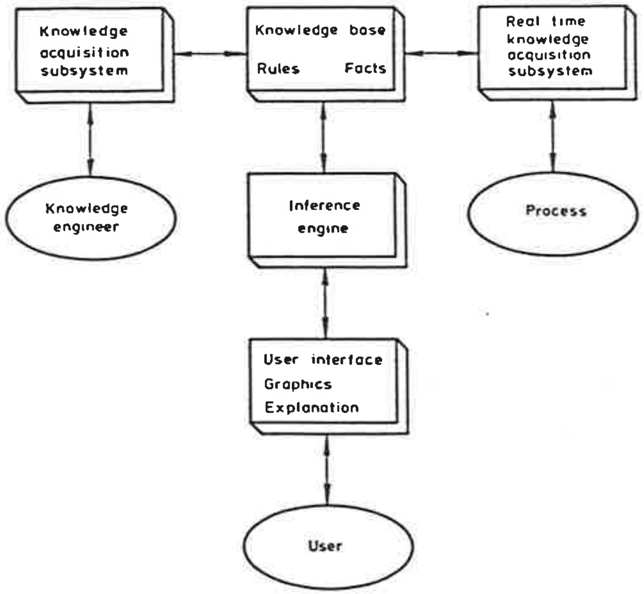

Fig. 10. A knowledge based expert system.

base, an inference engine and a user interface.

The Knowledge Base

The knowledge base consists of data and rules. The data can be separated into facts, and goals. Examples of facts are statements like "the control variable is in the range 0 to 50", "there is hysteresis in the actuator", "the system appears to be stable", "PI control is adequate", "deviations are normal". Typical examples of goals are "minimize the variations of the output", "maintain steady state control at specified limit", "find out if gain scheduling is necessary" or "find a scheduling table". Data is introduced into the database by the user or via the real time knowledge acquisition system. New facts can also be created by the rules.

The rulebase contains the production rules of the type: "if <premise> then <conclusion> do <action>". The <premise> represents facts or goals from the

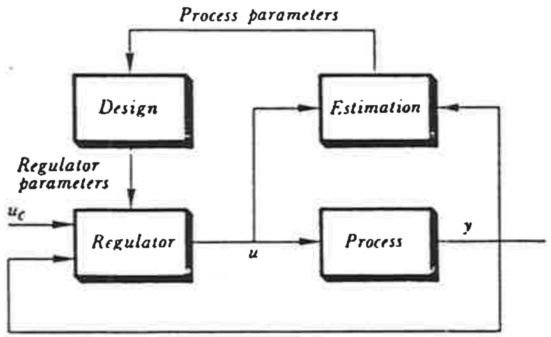

Fig. 6. Block diagram of a conventional adaptive regulator.

inherently will offer some insensitivity to modeling errors. Many different parameter estimation schemes have also been used, for example stochastic approximation, least squares, extended and generalized least squares, instrumental variables, extended Kalman filtering and the maximum likelihood method. See Åström (1983a) which gives an overview and many references. An example illustrates a typical case.

Example 1. Estimate the parameters of the second order model

$$y(t) + a_1y(t-h) + a_2y(t-2h) = b_1u(t-h) + b_2u(t-2h) \tag{3}$$

recursively. Let $\hat{a}_i$ and $\hat{b}_i$ denote the parameter estimates. The control law

$$u(t) = t_0r(t) - s_0y(t) - s_1y(t-h) - r_1u(t-h)$$

where

$$t_0 = (1+p_1+p_2)/(\hat{b}_1+\hat{b}_2)$$

$$r_1 = [(p_1-\hat{a}_1)\hat{b}_2^2 - (p_2-\hat{a}_2)\hat{b}_1\hat{b}_2]/N$$

$$s_0 = [(p_1-\hat{a}_1)(\hat{a}_2\hat{b}_1-\hat{a}_1\hat{b}_2) + (p_2-\hat{a}_2)\hat{b}_2]/N$$

$$s_1 = -\hat{a}_2r_1/\hat{b}_2$$

$$N = \hat{b}_2^2 - \hat{a}_1\hat{b}_1\hat{b}_2 + \hat{a}_2\hat{b}_1^2$$

gives a closed loop system whose pulse transfer function from the command signal to the output is given by

$$H_m(z) = \frac{1 + p_1 + p_2}{b_1 + b_2} \cdot \frac{b_1 z + b_2}{z^2 + p_1 z + p_2}$$

where

$$p_1 = - 2 e^{-\zeta\omega h} \cos \omega h \sqrt{1 - \zeta^2}$$

and

$$p_2 = e^{-2\zeta\omega h}$$

The closed loop system will thus retain the open loop zero and the closed loop poles correspond to a sampled second order system with bandwidth ω and relative damping ζ. □

Some minor modifications of the control law in the example are needed to handle bias and integral action. A detailed discussion of these factors is given in Åström (1979). The commercial regulators, Electromax V and TCS 6355 are based on estimation of parameters in the model (3). They do, however, use control design methods which are different from the one used in the example.

The self-tuner shown in Fig. 6 is called an indirect selftuner or an STR based on estimation of an explicit process model. It is sometimes possible to reparameterize the process so that it can be expressed in terms of the regulator parameters. This gives a significant simplification of the algorithm because the design calculations are eliminated. In terms of Fig. 5 the block labelled design calculations disappears and the regulator parameters are updated directly. This idea was used in the self-tuning regulator which is based on minimum variance control and least squares parameter estimation given in Åström and Wittenmark (1973). An example illustrates the idea which is also used in the ASEA Novatune.

Example 2. The self-tuner discussed in Åström and Wittenmark (1973) is based on the mathematical model

$$\begin{aligned} y(k+d) = {} & s_0 y(k) + s_1 y(k-1) + \ldots + s_{n_s} y(k-n_s) \\ & + r_0 u(k) + \ldots + r_{n_r} u(k-n_r) + \varepsilon(k+d) \end{aligned} \quad (4)$$

signal has sufficient energy content around the cross-over frequency and that it is so rich in frequency that it is persistently exciting. To guarantee a good model it is thus necessary to monitor the excitation and the energy of the input signal in the relevant frequency bands. A more detailed discussion is found in Åström (1984).

6. EXPERT CONTROL

The properties of auto-tuners and adaptive regulators are complimentary. The auto-tuner requires little prior information. It is very robust and it can generate good parameters for a simple control law. Adaptive regulators like model reference adaptive controllers or self-tuning regulators can use more complex control laws with potentially better performance. The self-tuners have local gradient procedures. Starting from reasonably good a priori guesses of system order, sampling period, and parameters, the algorithms can adjust the regulator parameters to give a closed loop system with very good performance. The algorithms will however not work if the prior guesses are too far off. With poor prior data they may even give unstable closed loop systems. This has led to the development of the safety jackets mentioned previously. The adaptive algorithms are also capable of tracking a system provided that the parameters do not change too quickly. It thus seems natural to try to combine auto-tuners and adaptive control algorithm. In Åström and Anton (1984) and Åström et al. (1986) it was proposed to use an expert system for this purpose.

Expert Systems

One objective for expert systems is to develop computer-based models for problem solving which are different from physical modeling and parameter estimation. See Barr and Feigenbaum (1982), Davis (1982), and Hayes-Roth et al. (1983) It attempts to model the knowledge and procedures used by a human expert in solving problems within a well-defined domain. Knowledge representation is a key issue in expert systems. Many different approaches have been attempted such as first order predicate calculus (logic), procedural representations, semantic networks, production systems or rules, and frames. The architecture of a knowledge-based is shown in Fig. 10. It consists of a knowledge regulators with logic selectors which brings up additional nonlinear problems. An operational industrial PID regulator thus consists of an implementation of the Equation (16) and some heuristic logic that takes care of the problems mentioned above. Although these heuristic factors are of extreme importance for good control they have not attracted much interest from theoreticians. They are instead hidden in practical designs and rarely discussed in the control literature. One reason for this is commercial secrecy, another is that most control engineers, being thoroughly indoctrinated by linear system theory, are poorly equipped to understand nonlinear phenomena. We can thus conclude that practical PID control is not solved by linear theory alone, but that nonlinearities plays an important role. They are typically handled by logic that surrounds the linear control law given by Equation (16). The logic is often designed heuristically.

Heuristic logic is even more important in adaptive control. The fundamental control law is much more complicated in this case. Windup can occur not only in the integrator but also in the estimator. Since there is a parameter estimator in the loop it is also necessary to safeguard against poor performance of the estimator due to poor data e.g. during an instrument failure. The adaptive algorithms also require some amount of apriori information. An example of the information needed to apply a general adaptive regulator was given in Section 3. To acquire this information it may be necessary to carry out a preliminary system identification phase. An empirical evidence of this is the pre-tune phase which exist in several commercial systems. To obtain a well functioning adaptive control system it is necessary to provide it with a considerable amount of heuristic logic. This goes under many names like safety nets or safety jackets. Experience has shown that it is quite time consuming to design and test this heuristic logic. Some practical issues are discussed in Wittenmark and Åström (1984). It is difficult to get information about what is actually done in practical systems because the manufacturers of adaptive systems are therefore understandably reluctant to disclose their tricks.

The key issues to get a robust controller are good data and an appropriate model structure. It is important that the model is accurate at the cross-over frequency. To obtain a good reduced order model it is essential that the input

where u is the control variable, y the measured output and ε is a disturbance. If ε is independent of the other terms on the right hand side the minimum variance control law for the plant (4) is simply

$$u(k) = -[s_0 y(k) + s_1 y(k-1) + \ldots + s_{n_s} y(k-n_s) + r_1 u(k-1) + \ldots + r_{n_r} u(k-n_r)]/r_0 \tag{5}$$

The basic self-tuning algorithm can be described as follows:

<u>Algorithm</u>. Repeat the following steps at each sampling period:

Step 1. Update the estimates of the parameters of the model (4), so that a weighted sum of squares of the errors ε are minimal.

Step 2. Compute the control signal u(k) from past data y(k), y(k-1),...,u(k-1),... using (5) with the estimates obtained from Step 1. □

Notice that when least squares estimation is used the error $\varepsilon(k+d)$ will be uncorrelated with the other terms in the right hand side of (4). Also notice that no design calculations are required since the parameters of the regulator (5) are obtained directly from the model parameters because of the special model structure used in (4).

<u>Direct and Indirect Adaptive Control</u>

An advantage of indirect adaptive control is that many different design methods can be used. The key issue in analysis of the indirect schemes is to show that the parameter estimates converge. This will in general require that the model structure used is appropriate and that the input signal is persistently exciting. To ensure this it may be necessary to introduce perturbation signals. The direct adaptive control schemes are simpler than the direct schemes. They may also work well even if the model structure used is not correct. The direct schemes will, however, require other assumptions.

<u>Prior Knowledge</u>

The parameter estimation step is a crucial part in all adaptive schemes. The sampling period is a critical parameter when discrete time models are fitted to data. The parameter estimation is insensitive to the sampling period if the true system is actually governed by a low order model. The sampling period is however critical when a low order model is fitted to a high order process. A low order model can be a very good approximation of a high order system if the sampling period is reasonably long. Results for short sampling periods can, however, be very poor because the parameters b_1 and b_2 will be underestimated, the computed gain becomes too high and the closed loop unstable. Experience indicates that it is not possible to obtain a good model (3) unless the order of magnitude of the sampling period is known. This means that it is not possible to construct a universal regulator for process control based on (3) unless some device for finding the sampling period is devised. For the regulator in Example 1 this can be achieved by relating the sampling period to the desired bandwidth and letting the operator choose it. The adaptive systems Electromax V and TCS 6355 both require prior knowledge of a time scale which among others is used to set the sampling period. A fairly elaborate "pretune" scheme is provided to determine the time scale by experimentation in both systems.

The self-tuning regulator given in Example 2 also requires prior knowledge. The following data is needed:

- h sampling period
- d delay in number of sampling periods
- n_r degree of the polynomial R
- n_s degree of the polynomial S
- λ forgetting factor
- θ_o initial estimate
- P_o initial covariance
- uh high control limits
- ul low control limits

The sampling period is critical as was discussed above. The integer d is also crucial. The closed loop system will become unstable if h and d are underestimated. The parameters are particularly important. Since the self-tuner is based on minimum variance control they will directly determine the closed loop bandwidth. The parameters n_r and n_s are not particularly critical. A

The gain will typically decrease as 1/t. For algorithms whose gains do not go to zero the estimates will fluctuate. The magnitude of the fluctuations decreases with decreasing gain. Selection of suitable gains in adaptive control algorithms is thus a compromize between tracking rate and precision. When discussing convergence rates it is also important to keep in mind that performance measures are approximately quadratic functions of the parameter errors.

Parameterization

Parameterization is an important issue which enters many aspects of the adaptive control problem. The number of parameters is important. With fewer parameters to estimate less requirements are imposed on the input signal to achieve persistent excitation. For direct adaptive control it is also important to have a model which is linear in the parameters was also emphasized. Different parameterizations will thus lead to systems having different characteristics.

Finally it is worthwhile to observe that the formulation of a generic model like (7) with all parameters unknown is often a poor model because in practice it often happens that part of the dynamics is known.

5. PRACTICAL ASPECTS

Some practical aspects on the implementation of adaptive regulators will be given in this section. An ordinary PID-regulator is first discussed to provide some perspective. This regulator is ideally described by

$$u(t) = \left[e(t) + \frac{1}{T_i}\int^{t} e(s)ds + T_d\frac{de(t)}{dt}\right] \qquad (16)$$

The linear behavior of PID-control can be understood very well from this equation. Suitable values of the parameters can be determined. The performance of the closed loop system can be predicted etc. The actual operation of a PID regulator must however take nonlinear behavior into account. It is thus necessary to consider switching between manual and automatic operation and transients due to parameter changes. The actuators will saturate for some period in virtually all applications. This gives rise to problems with windup of the integrator. It is also becoming increasingly more common to connect PID

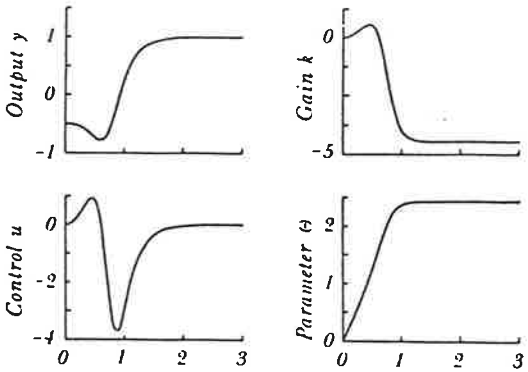

Fig. 9. Simulation of an integrator with Nussbaum's control law.

Convergence

The behavior of the parameters is an important issue in adaptive control. This is also a problem which has been the subject of much theoretical investigation. A typical approach is to assume that the system to be controlled is known and to investigate the behavior of the estimated parameters. The key problems have been investigated. Problems of this type have also been investigated in connection with determination of convergence conditions, possible convergence points and convergence rates. These problems have also been investigated in connection with system identification, see e.g. Åström and Eykhoff (1971). The result depends in complicated way on the process model, the disturbances and the estimation algorithm. There is, however, one complication in the adaptive case because the input to the process is generated by feedback. It is then more difficult to establish persistency of excitation. The feedback also makes the process input correlated with the disturbances.

A few simple observations can be made. If there are no disturbances, if the process input is persistently exciting and if the model structure is appropriate then the parameters can be determined exactly in a finite number of sampling periods. A recursive estimation algorithm which achieves this has time-variable gain. A constant gain algorithm will give exponential convergence. The situation is quite different when there are random disturbances. It is then necessary to have algorithms with decreasing gain in order to obtain estimates that converge.

calculation of covariances of inputs and outputs will show if they are too small, see Åström (1970). The parameter λ determines the trade-off between the tracking ability and the steady state variance of the recursive parameter estimator. The parameters θ_0 and P_0 determine the initial transient of the estimator but are otherwise unessential.

In control system design it is frequently necessary to make a trade-off between the response time and the size of the control signal. In minimum variance control this trade-off is made indirectly via selection of the sampling period. The regulator gain decreases and the response time increases with increasing sampling period. The minimum variance control law cannot handle nonminimum phase system because the process zeros are canceled by the controller. By increasing the sampling period and the delay d used in the adaptive control law the problems with nonminimum phase systems will, however, disappear. See Åström and Wittenmark (1985). Sampling of a stable system, with nonzero steady state gain, always gives a minimum phase sampled system provided the sampling period is sufficiently long. See Åström et al. (1984). This is also true for unstable systems provided that the unstability is caused by a single pole. The quality of the approximation by a low order system will also be improved when the sampling period is increased. The drawbacks with a long sampling period are slow responses to disturbances and changes in the set point. Notice that a sampled data system runs open loop between the sampling instants.

Predictive Control

There have recently been a considerable interest in adaptive regulators based on predictive control. Such regulators are based on estimation of models of the type

$$\begin{aligned} y(k+d) = {} & s_0 y(k) + s_1 y(k-1) + \ldots + s_{n_s} y(k-n_s) \\ & + r_{-d} u(k+d) + \ldots + r_{-1} u(k+1) \\ & + r_0 u(k) + \ldots + r_{n_r} u(k-n_r) + \varepsilon(k+d) \end{aligned} \tag{6}$$

The specifications are often expressed in terms of the desired step response of the closed loop system which is easy to describe to the operator. There are many different algorithms of this type e.g. the extended horizon minimum variance control (Ydstie, 1984) and extended prediction self-adaptive controls (de Keyser and Van Cauvenberghe, 1982, 1985; de Keyser et al., 1985). There are also variations based on linear quadratic optimization criteria. See Peterka (1984), the Musmar algorithm Mosca et al. (1982) and Lemos and Mosca (1985). These algorithms are also related to dynamic matrix control (Cutler and Ramaker, 1980) and model predictive control (Richalet et al., 1978), which is dealt with at length in Session III of this meeting. There are also multivariable extensions of the algorithms (Rouhani and Mehra, 1982).

4. THEORY

Theory has different roles in analysis and design of adaptive control systems. Analysis aimed at understanding specific algorithms is one goal. Creation of new adaptive control laws is another role. Adaptive systems are complex and difficult to analyse because they are inherently nonlinear. Progress in theory has been slow and much work remains before a reasonably complete coherent theory is available.

Because of the complex behavior of adaptive systems it is necessary to consider them from several points of view. Theories of nonlinear systems, stability, system identification, recursive estimation, convergence of stochastic algorithms and optimal stochastic control all contribute to the understanding of adaptive systems.

Generic Problems

A considerable effort has been devoted to construction of models which can serve as prototypes for general adaptive problems. The early work concentrated on systems where there was only a variation in the process gain. Much attention was later devoted to single-input single-output systems described by the equation

$$A(q)y(t) = B(q)u(t) + v(t) \tag{7}$$

In this model u is the control variable, y is the measured output and v is a

deal with uncertainties in the process model. A special class of systems were generated as attempts of solving the following problem which was proposed by Morse (1983). Consider the system

$$\frac{dy}{dt} = ay + bu$$

where a and b are unknown constants. Find a feedback law of the form

$$u = f(\theta,y)$$

$$\frac{d\theta}{dt} = g(\theta,y)$$

which stabilizes the system for all a and b. Morse conjectured that there are no rational f and g which stabilize the system. Morse's conjecture was proven by Nussbaum (1983) who also showed that there exist nonrational f and g which stabilize the system, e.g. the following functions

$$f(\theta,y) = (y-r)\ \theta^2 \cos\theta$$

$$g(\theta,y) = (y-r)^2$$

This correspond to proportional feedback with the gain

$$k = \theta^2 \cos\theta$$

The behavior of Nussbaum's regulator can be described as follows: Sweep the regulator gain k over positive and negative values. Find a way to stop the sweep rapidly if a stable system is obtained. Figure 9 shows a simulation of this control law applied to an integrator with unknown gain. Notice that the regulator is initialized so that the gain has the wrong sign. In spite of this the regulator recovers and changes the gain appropriately. Nussbaum's regulator is of considerable principal interest because it shows that the assumption A2 is not necessary. The control law is, however, not necessarily a good control law in a practical situation because it may generate quite violent control actions. The initial conditions for the simulation shown in Fig. 9 were in fact chosen quite carefully.

Nussbaums work has created a lot of interest. A clever multivariable extension is given by Mårtensson (1985 a,b).

gain k_y becomes too high. A device, which has been proposed to keep the parameters bounded, is to modify the equation for updating the parameters from

$$\frac{d\theta}{dt} = -k\varphi e$$

as in (9) to

$$\frac{d\theta}{dt} = -k\varphi e - \alpha\theta$$

This is referred to as introducing "leakage" in the estimator, see Ioannou and Kokotovic (1983). By stopping the updating when the error is small the drift of the parameters along the equilibrium line will also be eliminated. This is also referred to as a "dead zone". It was introduced in Egardt (1979) and has later been explored in Narendra and Petersen (1981). A technique of making the dead-zone adaptive is discussed in Goodwin (1986). All practical adaptive regulators have used some device of this nature to switch off the adaptation when there is little information to be gained from the process inputs and outputs.

System identification theory gives another way to explain the difficulty illustrated in Fig. 8. A step input is only persistently exciting of order 1. This means that only one parameter can be determined reliably and that any attempt to determine more parameters is futile. This can be used for diagnosis as discussed in Wittenmark and Åström (1984). It also suggests that the problem can be avoided by introducing perturbations which will allow all parameters to be reliably determined. This is discussed in Åström (1984). The usefulness of perturbations to gain useful information about the parameters is also suggested by dual control theory, see Åström (1983a).

Another interesting fact that has emerged from recent analysis is that there is a difference between the case of continuous time and discrete time regulators. In Rohrs et al. (1985) it is shown that unmodeled continuous dynamics is significantly reduced by the operation of sampling.

Universal Stabilizers

Adaptive control systems are nonlinear systems with a special structure. They are often designed based on the idea of automating modeling and design. It is natural to ask if there are other types of nonlinear controls which also can

disturbance. A and B are polynomials in the forward shift operator i.e.

$$A(q) = q^n + a_1 q^{n-1} + \ldots + a_n \quad \text{and} \quad B(q) = b_0 q^n + \ldots + b_m$$

Multivariable systems where u and y are vectors and A and B are matrix polynomials have also been explored.

The model (7) represents a system where the system dynamics is totally unknown. In many applications the situation is quite different because the system is partially known. This situation has not been investigated much because each problem has a special structure.

It is customary to separate the tuning and the adaptation problem. In the tuning problem it is assumed that the process to be controlled has constant but unknown parameters. In the adaptation problem it is assumed that the parameters are changing. Many issues are much easier to handle in the tuning problem. The convergence problem is to investigate if the parameters converge to their true values. The corresponding problem is much more difficult in the adaptive case because the targets are moving. The estimation algorithms are the same in tuning and adaptation. They can be described by

$$\theta(t+1) = \theta(t) + P(t)\psi(t)[y(t+1) - \varphi(t)\theta(t)] \tag{8}$$

The gain matrix P behaves, however, very differently in the two cases. It goes to zero in the tuning case as t increases but it does not converge to zero in the adaptive case.

Stability

Stability is a basic requirement on a control system. Much effort has also been devoted to analysis of stability of adaptive systems. It is important to keep in mind that the stability concepts for nonlinear differential equations refer to stability of a particular solution. It is thus often the case that one solution is stable and another one unstable.

Stability theory has been the major inspiration for the development of model reference adaptive systems. Many attempts were made to provide stability proofs during the seventies. Several crucial issues were however overlooked and it was not until 1980 that correct stability proofs appeared. See Egardt (1979), Fuchs (1979), Goodwin et al. (1980), Gawthrop (1980), de Larminat

(1979), Morse (1980), and Narendra et al. (1980). An elegant formalism for the proof has recently been published by Narendra and Annaswamy (1984).

Assumptions for stability proof. The following assumptions are essential for the stability proof.

(A1) the relative degree d = deg A - deg B is known,

(A2) the sign of the leading coefficient b_0 of the polynomial B(q) is known,

(A3) the estimated model is at least of the same order as the process,

(A4) the polynomial B has all zeros inside the unit disc.

The stability theorems are important because they give simple and rigorous analysis of a reasonable adaptive problems. The assumptions required are, however, very restrictive.

The assumption A1 means for discrete systems that the time delay is known with a resolution of one sampling period. This is not unreasonable. For continuous time systems the assumption means that the slope of the high frequency asymptote of the Bode diagram is known. Together with assumption (A2) it also means that the phase is known at high frequencies. If this is the case, it is possible to design a robust high gain regulator for the problem, see Horowitz (1963), Horowitz and Sidi (1973). For many systems like flexible aircraft, electromechanical servos and flexible robots, the main difficulty in control is the uncertainty of the dynamics at high frequencies, see Stein (1980).

The assumption A2 was believed necessary for a while. A clever demonstration that this was not the case was published by Nussbaum (1983). Further exploration of Nussbaums results have given rise to the notion of universal stabilizers which will be discussed in more detail below.

Assumption A3 is very restrictive, since it implies that the estimated model must be at least as complex as the true system, which may be nonlinear with distributed parameters. Almost all control systems are in fact designed based on strongly simplified models. High frequency dynamics are often neglected in the simplified models. It is therefore very important that a design method can cope with model uncertainty, see Horowitz (1963). It was demonstrated by Rohrs et al. (1982) that instabilities could easily be generated if the assumption A3 is violated. This has generated a lot of research into the robustness of adaptive

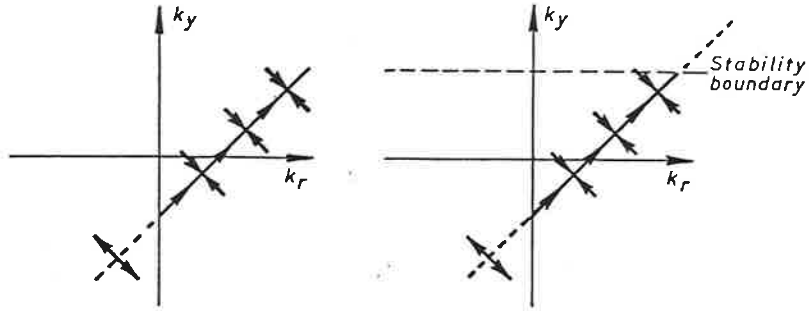

Fig. 8. Parameter trajectories of a model reference adaptive system with measurement noise.

be arbitrarily high if the initial conditions are chosen appropriately. This does not give rise to any problems in the nominal case. If the process to be controlled has additional dynamics which is not modeled by (15) like timedelays it may, however, be unstable when the feedback gain is sufficiently high. The closed loop system will then be unstable for sufficiently large initial values of the parameters as is shown in Fig. 7B. We can thus conclude that the adaptive system designed for a first order plant may be unstable when applied to a system with more complicated dynamics.

The case when there is measurement noise is shown in Fig. 8. The effect of measurement noise is that there will be a drift along the equilibrium line. The feedback gain will thus increase continuously . This will not give rise to difficulties in the nominal case. A plant with more complicated dynamics may, however, become unstable for high gains.

Having described the instability mechanisms we can now also discuss various measures used to improve the robustness. In Egardt (1979) it is shown that stability can, roughly speaking, be guaranteed even in the presence of disturbances by imposing one of the conditions

a) Parameters are bounded.

b) The parameters are not updated if the errors are small.

It seems intuitively reasonable that these conditions will help in the example discussed by keeping the parameters bounded we can avoid that the feedback

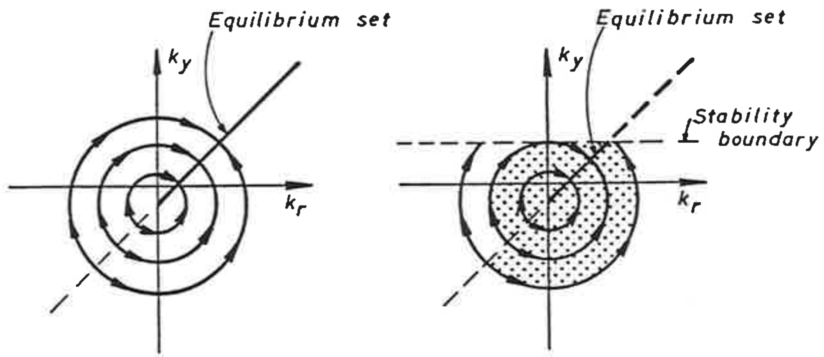

Fig. 7. Parameter trajectories for a model reference adaptive system with two parameters. Figure 7A shows the nominal case where the plant is of first order. Figure 7B shows the case when the plant is of higher order.

nominal plant be characterized by

$$G(s) = \frac{b}{s + a} \tag{15}$$

and the model by

$$G_m(s) = \frac{b_m}{s + a_m}$$

The closed loop system is then described by (9) with

$$\varphi = [r \quad -y]^T$$

$$\theta = [k_r \quad k_y]^T$$

If the command signal r is a step and if the adaptation is sufficiently small it was shown in Åström (1984) that the parameters follow the trajectories shown in Fig. 7A. A characteristic feature is that the equilibrium is not unique. The parameters can settle anywhere on the half-line shown in Fig. 7A. The reason for this is that the command signal is a step, which gives reliable information about the steady state gain. The parameters moves towards the equilibrium along arcs which are approximately circular. Notice also that the feedback gain k_y can

control. Several modifications of the algorithms have been proposed to improve robustness. One idea is to introduce a term $-a\theta$ to the right hand side of (8). This is called "leakage". Another idea is to filter the error and the regression vector φ in (8). A third idea is to introduce nonlinear modifications of the estimation algorithm. These issues are discussed at length in the monograph (Kosut et al., 1986).

Assumption A4 is also crucial. It arises from the necessity to have a model, which is linear in the parameters. It follows from the discussion in the Appendix that this is possible only if $B^- = b_0$. In other words the underlying design method is based on cancellation of all process zeros. Such a design will not work even for systems with known constant parameters if the system has an unstable inverse.

The analysis by Egardt (1979) also applies to the case when there are disturbances. Egardt has given counterexamples which show that modifications of the algorithms or additional assumptions are necessary if there are disturbances. One possibility is to bound the parameter estimates a priori for example by introducing a saturation in the estimator. Another possibility is to introduce a dead zone in the estimator which keeps the estimates constant if the residuals are small. These results also hold for continuous time systems as has also been shown by Peterson and Narendra (1982).

Instability Mechanisms

Apart from the stability proofs it is also useful to have an understanding of the mechanisms that may create instability. To develop this insight we will consider a simple model reference adaptive control problem which is described by the equations

$$\begin{aligned} y &= G(p)u \\ u &= \theta^T\varphi \\ \frac{d\theta}{dt} &= -k\varphi e \\ e &= y - y_m \end{aligned} \tag{9}$$

where u is the process input, y the process output, y_m the desired model output, e the error and θ a vector of adjustable parameters. The transfer function of the process is G and p = d/dt denotes the differential operator. The components of the vector φ are functions of the command signal, the system input and output. It follows from (9) that

$$\frac{d\theta}{dt} + k\varphi[G(p)\varphi^T\theta] = k\varphi y_m \tag{10}$$

This equation gives insight into the behavior of the system.

Slow adaptation. Assume first that the adaptation loop is much slower than the process dynamics. The parameters then change much slower than the regressive vector and the term $G(p)\varphi^T\theta$ in (9) can then be approximated by its average

$$G(p)\varphi^T\theta \approx \overline{[G(p)\varphi^T(\theta)]}\theta \tag{11}$$

Notice that the regression vector depends on the parameters. The following approximation to (10) is then obtained

$$\frac{d\theta}{dt} + \overline{k\varphi(\theta)[G(p)\varphi^T(\theta)]}\theta \approx k\varphi y_m \tag{12}$$

This is the normal situation because the adaptive algorithm is motivated by the fact the parameters change slower than the other variables in the system under this assumption. Notice, however, that it is not easy to guarantee this.

Equation (12) is stable if $k\varphi[G(p)\varphi^T]$ is positive. This is true e.g. if G is SPR and if the input signal is persistently exciting.

Fast Adaptation. The approximation (12) is based on the assumption that the parameters θ change much slower than the other system variables. If the parameters θ change faster than φ then (10) can be approximated by

$$\frac{d\theta}{dt} + k\varphi\varphi^T G(p)\theta \approx k\varphi y_m \tag{13}$$

A linearization for constant φ_0 shows that the stability is governed by the algebraic equation

$$\det[sI + k\varphi_0\varphi_0^T G(s)] = s^{n-1}[s+KG(s)] = 0 \tag{14}$$

where I is the identity matrix and K is given by

$$K = k\varphi_0^T \varphi_0$$

is the equivalent adaptive loop gain. The stability can then be determined by a simple root-locus argument.

For sufficiently large $k\varphi_0^T\varphi_0$ the system will always be unstable if the pole-excess of G(s) is larger than or equal to 2. Also notice that the equivalent gain K is proportional to $\varphi_0^T\varphi_0$. The equivalent gain can thus be made arbitrarily large by choosing the command signal large enough. It thus seems intuitively clear that the adaptive system can be made unstable by making the command signal large enough.

Once the source of the difficulty is recognized it is easy to find a remedy. Since the equivalent gain K in the adaptive loop is too large because of its signal dependence, one possibility is simply to modify the parameter updating law to

$$\frac{d\theta}{dt} = -\frac{k}{1+\varphi^T\varphi}\varphi e$$

Equation (13) then holds with

$$K = k\frac{\varphi\varphi^T}{1+\varphi^T\varphi}$$

The equivalent gain in the adaptation loop is then bounded and the parameters θ will change arbitrarily slow for all signal levels. The actual value of the k can be chosen based on a simple root-locus argument for (14).

The modification of the parameter updating law has been used by many authors e.g. Narendra and Lin (1980). It is also worthwhile to note that a law of this type is obtained automatically when adaptive laws are derived from recursive estimation, see Åström (1983b). The high gain instability mechanism is the same as the one discussed in Cyr et al. (1983).

An Example

Many of the robustness issues can be illustrated by a simple example. Consider model reference adaptive control of a first order system. Let the