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Åström, Karl Johan

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LUND UNIVERSITY

PO Box 117
221 00 Lund
+46 46-222 00 00

LUND INSTITUTE OF TECHNOLOGY
DEPARTMENT OF AUTOMATIC CONTROL
Box 725
S 220 07 Lund 7 Sweden

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Karl Johan Åström

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LQG SELF-TUNERS

Karl Johan Åström

Department of Automatic Control, Lund Institute of Technology
Box 725, S-220 07 Lund 7, Sweden

Abstract. This paper surveys self-tuning regulators based on linear quadratic gaussian (LQG) control design and recursive parameter estimation. Only single-input single-output systems are considered. The linear quadratic design method is reviewed. Theoretical issues like convergence, persistent excitation and closed loop identifiability are discussed. Special attention is given to the robustness issues. An application is also given

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1. INTRODUCTION

Self-tuning regulators are based on a very simple heuristic idea. A design problem is first solved under the assumption that a model of the system and its environment is known. When the parameters are not known they are replaced by estimates obtained from a recursive parameter estimator. Self-tuning regulators where the underlying design scheme is based on linear quadratic gaussian (LQG) control theory are discussed in this paper. One advantage by this formulation is that the performance of the control system can be characterized by a few parameters. In the single-input single-output case there is in fact only two parameters: the sampling period and the weighting factor between penalty on the control signal and the output error. Another advantage is that the LQG theory is not restricted to any particular class of systems. It can thus easily be applied to non-minimum phase systems as well as to systems with variable time delays.

A self-tuner based on LQG was first proposed by Peterka and Åström (1973). The solution was based on an interactive solution of the steady state Riccati equation. This idea was further elaborated by Åström (1974), Åström and Wittenmark (1975), Gustavsson (1980), Samson (1980), Belanger (1981), and Zhao-Ying and Åström (1981). Closely related approaches have been proposed by Mosca and Zappa (1980), Menga and Mosca (1980), Trulsson and Ljung (1982).

There are comparatively few theoretical results on LQG self-tuners. The closed loop identifiability problems are discussed by Kumar (1981). A convergence proof is due to Moore (1983). Applications of LQG self-tuners have been described in Åström (1980c) and Åström and Zhao-Ying (1982).

This paper is organized as follows. The LQG design for system with known parameters is reviewed in Section 2. A polynomial approach is convenient because the treatment is limited to single-input single-output systems. The polynomial approach is also useful because it is based on a model structure which is suitable for parameter estimation. Recursive estimation is discussed in Section 3. The results of Sections 2 and 3 are combined in Section 4 which deals with LQG self-tuning algorithms. Theoretical issues are discussed in Section 5. Robustness is discussed in Section 6, where new devices to ensure robustness are proposed. An application to concentration control is given in Section 7. This illustrates some of the advantages of the LQG approach.

2. LQG DESIGN

The LQG design for systems with known parameters is reviewed in this

Section. This material is well-known in text books. See e.g. Åström (1970) or Åström and Wittenmark (1984). The problem can be formulated either in terms of state models or input-output models. The input-output formulation is convenient for our purposes. Consider a single-input single-output system described by the model

$$A(q)y(t) = B(q)u(t) + C(q)e(t) \qquad (2.1)$$

where q is the forward shift operator.

Let the criterion be to minimize

$$E \lim_{t\to\infty} \frac{1}{t} \sum_{k=1}^{t} [y^2(k) + \varrho\, u^2(k)] \qquad (2.2)$$

Notice that the sampling period h is a hidden parameter in this formulation. A better formulation would be to use the continuous time criterion.

$$E \lim_{t\to\infty} \frac{1}{t} \int_0^t [y^2(s) + \varrho' u^2(s)]ds \qquad (2.2')$$

which is independent of the sampling period. For a sampled system the criterion (2.2') can be transformed to (2.2). The parameter ϱ will, however, depend on the sampling period h. There will also be a cross term $y(k)u(k)$ in (2.2). See Åström (1970). We will however use the simplified formulation (2.2).

The optimal feedback law which minimizes (2.2) for (2.1) is given by the following theorem

THEOREM 1

Consider the system (2.1). Let the polynomials A(z) and C(z) have degrees n. Assume that C(z) has all its zeros inside the unit disc and assume that there is no polynomial which divides A(z), B(z) and C(z). Let $A_2(z)$ be the greatest common divisor of A(z) and B(z) and let $A_2^-(z)$ of degree m, be the factor of $A_2(z)$ which has all its zeros outside the unit disc or on the unit circle. The admissible control law which minimizes (2.2) with $\varrho>0$ is then given by

$$R(q)u(t) = - S(q)y(t) + T(q)u_c(t) \qquad (2.3)$$

where the polynomials R and S satisfy the Diophantine equation

$$A(z)R(z) + B(z)S(z) = P(z)C(z) \qquad (2.4)$$

with the additional constraints

(i) $\deg R(z) = \deg S(z) = n+m$

(ii) $A_2^-(z)$ divides $R(z)$

(iii) $\deg S^*(z) < n$

The polynomial P(z) is given by

$$P(z) = z^m P_1(z)\, A_2(z) \qquad (2.5)$$

where

$$P_1(z)P_1(z^{-1}) = \varrho A_1(z)A_1(z^{-1}) + B_1(z)B_1(z^{-1}) \qquad (2.6)$$

and

$$A_1(z) = A(z)/A_2(z)$$

$$B_1(z) = B(z)/A_2(z)$$

The polynomial T(z) is given by

$$T(z) = t_o\, z^m\, C(z) \qquad (2.7)$$

where

$$t_o = P_1(1)/B_1(1)$$

□

A proof of Theorem 1 is given in Åström and Wittenmark (1984).

Algorithms

To solve the design problem it is necessary to solve the spectral factorization problem (2.6) and to solve the Diophantive equation (2.4). The spectral factorization problem can be solved by the algorithm due to Wilson (1969) which has been retired by Vostry (1975). This algorithm is iterative and has the advantage that the polynomial P, obtained at each step is guaranteed to be stable. The Diophantine equation can be solved by the Euclidean algorithm. This algorithm has the advantage that it also detects common factors in the polynomials A and B. A neat implementation at the Euclidean algorithm is given by Blankinship (1963). Additional material on algorithms for solving the spectral factorization problem and the Diophantine equation are given in Kucera (1979).

Alternative approaches

An alternative solution to the design problem is to use the state space formulation. The control law is then obtained in terms of solutions of Riccati equations for the feed back gain and the Kalman filer. This approach is described in detail in the text books by Anderson and Moore (1971) and Åström (1970).

Relations to pole placement

The solution to the LQG problem given by Theorem 1 has close relations to the pole placement design problems. The solution to the spectral factorization problem gives the closed loop poles. The second step in the algorithm can be interpreted as a pole placement problem.

It is clear from the description of the design algorithm that a pole placement self-tuner is obtained as a by-product, simply by specifying the polynomial P instead of determining it from spectral factorization.

3. PARAMETER ESTIMATION

When the parameters of the model (2.1) are not known they can be estimated recursively by the extended least squares (ELS) method or by recursive maximum likelihood (RML). A detailed description of these methods are given in Ljung and Söderström (1983). For simplicity we will here describe the ELS algorithm. Introduce

$$\theta = [\, a_1 \dots a_n \; b_1 \dots b_m \; c_1 \dots c_\ell \,]^T$$

$$\begin{aligned}\varphi(t) = [\, & -y(t-1) \; \dots \; -y(t-n) \\ & u(t-1) \; \dots \; u(t-m) \\ & \varepsilon(t-1) \; \dots \; \varepsilon(t-\ell) \,]^T\end{aligned}$$

and

$$\varepsilon(t+1) = y(t+1) - \varphi^T(t+1)\,\theta(t).$$

The extended least squares algorithm Panuska (1969) is given by

$$\theta(t+1) = \theta(t) + K(t+1)\varepsilon(t+1)$$

$$K(t+1) = \frac{P(t)\,\varphi(t+1)}{1 + \varphi^T(t+1)\,P(t)\,\varphi(t+1)}$$

$$P(t+1) = \frac{1}{\lambda}\left[P(t) - \frac{P(t)\varphi(t+1)\varphi(t+1)^T P(t)}{\lambda + \varphi(t+1)^T P(t)\varphi(t+1)}\right] \tag{3.1}$$

In actual implementation a square root algorithm based on the U-D algorithm is preferable. See Bierman (1977). The number λ in (3.1) is a forgetting factor introduced to discount past data. A better way of discounting old data is given by Hägglund (1983).

4. SELF-TUNING CONTROL

A block-diagram of a general self-tuner is shown in Fig. 1. It can be viewed as an on-line automated design.

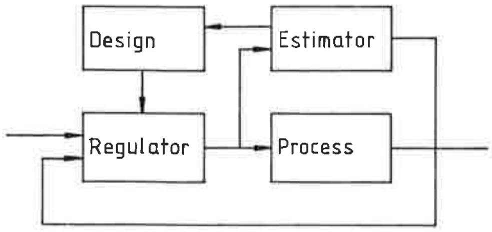

Fig. 1. - Block diagram of a self-tuner.

In the LQG self-tuner the design is a solution to the LQG design problem and the parameter estimator is a recursive estimator like the one discussed in Section 3.

Solution of the Riccati equation or the spectral factorization is the major computation in an LQG self-tuner. This calculation can be made in several different ways. The Riccati equation can be solved by the eigenvalue method due to Potter (1966) or by some iterative method, ordinary time iterations or by the method proposed by Kleinman (1968). The iterative methods will in general lead to shorter code. It is however difficult to cope with iterations in an on-line algorithm. To guarantee that the calculations can be performed in a prescribed sampling period it is necessary to truncate the iterations. It is then a necessity to guarantee that a sensible iterate is obtained when the iteration is truncated. The particular method based on spectral factorization using Wilson's algorithm which is discussed in Section 2 has the advantage that the polynomial P obtained at each iteration is stable.

Programming and coding

Several different versions of the LQG self-tuner have been coded in Pascal for the DEC LSI 11/03. An implementation of the algorithms described in Sections 2 and 3 are described by Åström and Zhao-ying (1982). The source code is about 1400 lines of Pascal. This includes comments and declarations. The total size of the compiled code is about 40 kbytes. In the coding flexibility and readability has been emphasized rather than compactness and computational speed.

Another implementation based on the solution of Riccati equation was given in Åström (1974). In this code there was no operator communication.

The pure foreground code compiled to about 8 kbytes on a DEC PDP-15. Another program for the DEC LSI 11/03 written in Fortran by Gustavsson (1980) has a source code of about 1400 lines. Half of them are comments. The compiled code required about 40 kbytes. Of these about 8 kbytes was required for the pure foreground.

It thus appears that implementations based on Riccati equations and polynomial manipulations require about the same amount of code. The minimum size of a dedicated implementation with no operator communication is about 8 kbytes.

5. THEORETICAL ISSUES

The key theoretical problems for adaptive control are stability, convergence and performance. These questions are reasonably well understood for the simple self-tuners based on least squares estimation and minimum variance control, where conditions for global and local convergence are known. Much less is known about the algorithm discussed in this paper. Some available results will be discussed in this Section.

Parameter Estimation

Estimation of the parameters in the model (2.1) is complicated even in the off-line case, because it is non-linear in the parameters. See Åström and Bohlin (1965). When there are no input signals it is shown in Åström and Söderström (1974) that the asymptotic likelihood function obtained for large data sets is unimodal. The likelihood function may, however, have local minima when there are inputs even if they are persistently exciting.

The difficulties associated with local minima of the likelihood function are also inherited by the recursive algorithms ELS and RML. It follows from the general results on convergence of recursive algorithms that they may have the local minima as equilibrium points. See Solo (1979) and Ljung and Söderström (1983). The new recursive algorithm proposed by Åström and Mayne (1982) may perhaps avoid this difficulty.

Persistent Excitation

To ensure a unique minimum it is necessary that the input signal is persistently exciting. See Åström and Bohlin (1965). This is difficult to ensure when the input signal is generated by feedback unless extra perturbations are introduced or parameters are updated only when there is proper excitation. These issues are discussed further in Section 6 when it is mentioned that excitation should be obtained by signals in a certain frequency range. Compare also the notion of dominant excitation in Ioannou and Kokotovic (1983).

Identification in closed loop

Identifiability may also be lost because identification is made in closed loop. See Åström and Eykhoff (1971) and Ljung et al (1974). Kumar (1981) has shown that serious difficulties may arise at least in the case when the parameters belong to a finite set. For a first order system it is shown that there is an equilibrium set for the parameters, for the LQG self-tuner, where only one point correspond to the optimal solution. This is different from the minimum variance self-tuner where all points in the equilibrium set give the optimal feedback. It is not clear what happens in the general case. My conjecture is that the parameters may converge to the limit set at the rate of 1/t, and then move towards the correct solution a rate of 1/(log t). This is hard to analyse because the phenomena can not be captured by the ordinary differential equations given by Ljung (1977).

Kumar has suggested a modification of the least squares criterion, which gives a feedback law that converges to the true LQG solution even when the parameters are in a discrete set.

Results for the case of discrete parameters are also given by Hijab (1983).

There are also other significant differences between the case of finite and continuous parameter sets.

Loss of identifiability due to feedback can also be reduced by introducing an additional delay in the regulator or by introducing perturbation signals. Moore (1983) has an algorithm which is claimed to converge globally.

Direct algorithms

The algorithm given in Section 4 is indirect because it is based on estimation of parameters of a process model. For simpler adaptive schemes there direct algorithms where the regulator parameters are updated directly. These algorithms can be obtained from a reparameterization of the process model. See e.g. Åström (1980a). Several attempts have been made to derive direct algorithms for LQG self-tuners. Trulsson and Ljung (1982) have suggested to use the gradient approach suggested by Tsypkin (1971). The algorithms obtained in this way have the same complexity as the algorithms in Section 4.

Another approach called MUSMAR is suggested by Menga and Mosca (1980) and Mosca and Zappa (1980). Their direct algorithm reduces to two least squares calculations. A further simplification of this scheme is proposed by Bartolini et al (1982).

6. ROBUSTNESS

A control system should be insensitive to measurement errors, disturbances and modeling errors. Although these issues are important for all control systems they have only lately been considered in connection with adaptive systems. See Rohrs et al (1982) and Ioannu and Koktovic (1983).

A discussion of the central problems for the adaptive LQG regulator are given in this Section. The robustness of the underlying design problem, the recursive estimator and the combined problem are discussed.

Robust Control Design

Robustness properties are conveniently discussed in terms of the loop gain. See the Bbode plot of a typical loop gain in Fig. 2. The loop gain is unity at the cross-over frequency ω_c. A common engineering practice which is now well supported by theory Horowitz (1963), Doyle and Stein (1981) and Lehtomahi et al (1981) boils down to the following: Make the loop gain high below the cross-over frequency and make sure that the loop gain falls off rapidly above the cross-over frequency. A high loop gain for low frequencies is obtained by introducing integral action or some resonant system which gives a high gain for special frequency bounds as is indicated in Fig. 2. The rapid roll-off for high frequencies is necessary to ensure that unmodeled high frequency dynamics will not cause difficulties. Computer controlled systems should always be provided with antialiasing filters to eliminate signal transmission above the Nyquist frequency. A well designed digital regulator will thus not have any signal transmission above the Nyquist frequency. The high frequency roll-off for a digital regulator is thus significantly influenced by the sampling period.

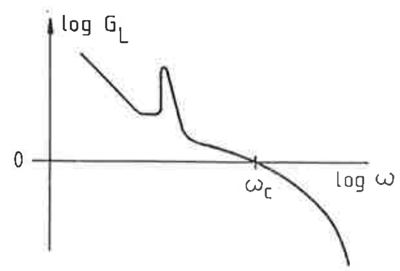

Fig. 2. - Bode diagram of the loop gain.

A quantitative statement of the above discussion for the LQG design can be obtained as follows. Assume that a LQG regulator based on the model (2.1) is designed for a system with the true pulse transfer function G_o. The following result then holds.

THEOREM 2

Consider a system with the pulse transfer function G_o. Let a regulator (2.3) be designed based on the approximate model (2.1). Assume that G_o and $G=B/A$ have the same number of unstable poles. The closed loop system obtained is the stable if

$$\left| G_o - G \right| < \left| \frac{G}{G_m} \right| \cdot \left| \frac{T}{S} \right| \qquad (6.1)$$

on the unit circle and at infinity □

The theorem is proven in Åström (1980d). The left-hand side is the relative error in the pulse transfer function. The right-hand side contains quantities which can be computed when the design calculation have been performed. Notice that G is the open loop pulse transfer function of the plant model and that G_m is the pulse transfer function from the command signal to the output.

The detailed character of the inequality (6.1) is highly problem dependent. Some general characteristics can, however, be found by inspection. The right hand side of (6.1) is small when G is less than G_m i.e. when the open loop gain is less than the model gain. This is the case for frequencies around the cross-over frequency. Theorem 2 thus indicates that it is necessary to have a model which gives an accurate description of the process around the cross-over frequency.

Robust estimation

When a parameter estimator is used in an adaptive scheme like the one shown in Fig.1. it is important to make sure that good estimates are obtained. Bad data should not generate poor estimates.

A special feature of the adaptive control application is that a low order model is fitted for a complex plant. The model obtained in such a case will critically depend on the frequency content of the input signal. It was e.g. shown by Mannerfelt (1981) that with pure sinusoidal excitation the transfer function will agree exactly with the plant transfer function at the excitation frequency. To guarantee a stable operation it follows from Theorem 1 that a certain precision of the model is needed around the cross-over frequency. To ensure this it is therefore necessary that the input signal has a sufficient energy content in that frequency band. This can be monitored using the system shown in Fig.3. The conditions for persistent excitation, Åström and Bohlin (1965) can be monitured instead of the signal energies as shown in Fig.3.

If the useful signal to noise ratio is to low there are two options: Excitation signals may be introduced or the parameter estimation may be switched off. Guided by the results of Egardt (1979) and Narendra and Peterson (1980) it is also reasonable to estimate ouly when the absolute level of the useful input energy is above a certain level. These safe-guards can be regarded as an implementation of the common sense rule: Do not estimate unless the data is good.

There are other safe-guards of a similar nature to make sure that the data used for estimation is always good by excitation or that the parameter estimation is only made when the data is reasonable. The difficulties noticed by Rohrs and others (1982) will not arise if those parameters are taken.

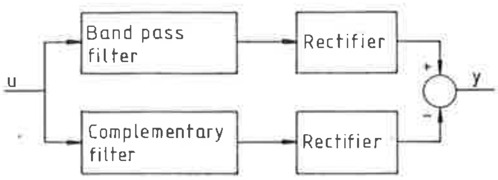

Fig. 3. - Circuit for monitoring the signal to noise ratio for estimating a reduced order model

Robust adaptive control

To obtain a robust adaptive control algorithm it is necessary to use both robust control and robust estimation. In the adaptive problem there are also some new trade-offs to be made. Consider for example the robustness properties obtained by having a high open loop gain at low frequencies. This may be obtained by having integral action in the control loop. It can also be obtained via adaptation. An adaptive regulator with enough parameters will automatically introduce a high gain at those frequencies where there are low frequency disturbances.

I have often found it beneficial to use a design method which gives a high gain at low frequencies and use adaption only to find the characteristics around the cross-over frequency. This has the additional advantage that fewer parameters are needed. It speeds up the estimation, and the degrees of the polynomials are kept low which improves the inherent numerical problems with polynomial representation. One possibility is to estimate a model of the type

$$A(q)\nabla y(t) = B(q)\nabla u(t-1) + C(q)e(t) \qquad (6.2)$$

where $\nabla = q - 1$ is a difference operator. Provided that $C(1) \neq 1$ this model implies that there are drifting disturbances. A consequence of this is that the regulator designed from (6.2) will always have a high gain at low frequencies. See Åström (1982).

7. AN APPLICATION

Some practical aspects on the LQG-tuner will be given in this section. Since the LQG self-tuner is more complicated than the simple self-tuners based on least squares and minimum variance control it is legitimate to question the benefits of the increased complexity.

Trading input and output variances

Although the output variance is often of major interest in process control applications it is also important to make sure that the variance of the control variable is reasonable. For the simple self-tuner the trade-off between input and output variances is governed by the selection of the sampling period h and the prediction horizon d. It is thus necessary to use two design parameters. It has been demonstrated by Toivonen (1981) that there are limitations in this approach.

Clarke and Gawthrop (1975, 1979) have proposed another way to deal with the problem. They use a criterion of the type (2.2) where the sum has one term only. This captures part of the problem. Because of the short time horizon there is however no guarantee that a stable System is obtained. See Moden and Söderström (1982).

The LQG self-tuner does not suffer from any of the drawbacks discussed above because it is based on an infinite horizon solution to the LQG problem. The LQG self-tuner is of course also well suited for those rare problems where there is a natural LQG formulation. See Åström (1980c).

Non minimum-phase plants

The simple self-tuner can not be applied to a plant where the sampled model is not minimum-phase, because the design is based on cancellation of the process zeros. This may seem restrictive at first. It is, however, shown in Åström et al (1983) that any stable plant which is sampled with a sufficiently long period will result in a sampled model which is minimum phase. The simple self-tuner can thus always be used for stable systems if the sampling period is long enough. The LQG self-tuner has no difficulties with non-minimum phase systems because the underlying design method is not based on cancellation of process zeros.

Time delays

For the simple self-tuner it is necessary to know an upper bound of the process dead-time. This is not needed for the LQG self-tuner. The problem is circumvented simply by having a large number of b-parameters in the model. It does not matter in the design if the leading b-parameters are zero. The LQG self-tuner thus has significant advantages if there are significant variations in the time-delay.

An Example

The properties of the LQG self-tuner are illustrated by an application to concentration control.

Tap water flows through a mixing chamber where it is mixed with a concentrated salt solution. The flow rate of the salt solution is controlled by a pump. The water then flows through a long tube and a stirred tank. The concentration at the outlet is measured with a conductivity cell. The outlet flow may also be recirculated to the input. The amount of recirculation can be adjusted. The control variable is the speed of the pump. The controlled variable is the concentration at the outlet. The dynamics varies with the flow rate because the time-delay and the time-constants are inversely proportional to the flow rate. The process gain is directly proportional to the concentration of the salt solution and inversely proportional to the flow.

The impulse responses of the system at different flow rates are shown in Fig. 4. The figure shows clearly that there is a substantial variation of the dynamics with the flow rate. Notice in particular the response obtained with recirculation.

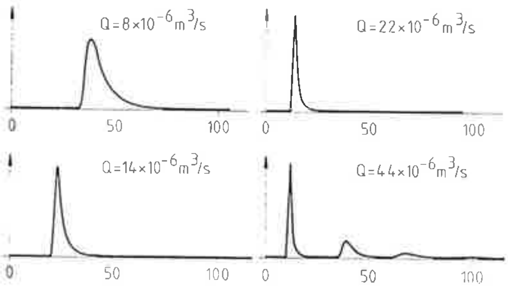

Fig. 4. - Impulse responses of the process for different flow rates.

The process dynamics can be approximatively described by the model

$$y(t)+ay(t-1)=b_d u(t-d)+b_{d+1}u(t-d-1)$$

where the sampling period is chosen as the time unit and the integer d is such that the time-delay is between dh and dh+h.

Since the number d is not known a priori the following model is used

$$y(t)+a_1 y(t-1)=b_1 u(t-1)+...+b_r u(t-r)$$

where $r > d$ is determined from an estimate of the largest time-delay. Experience showed that the uncertainty in the parameter estimates increase with r. The actual numbers depend critically on the character of the input signal.

Fig. 5 shows that a regulator with constant parameters will not work well if there are large flow changes. The flow is first set to 14×10^{-6} m^3/s. The process then has a time constant of 13 s and a time delay of 17 s. The curves labeled fixed gain show results when the self-tuner is run for about 30 sampling periods. The regulator parameters are then fixed and the flow is changed. It is seen from the Fig. 5 that the regulator behaves well when the flow is increased to 22×10^{-6} m^3/s. When the flow is decreased to 10×10^{-6} m^3/s the damping decreases. The control loop becomes unstable when the flow is further decreased to 8×10^{-6} m^3/s. The results are natural because the time-delay and the time constants increase with decreasing flow. When the flow is sufficiently small the time delay is so large that the system becomes unstable.

Results from experiments with an LQG self-tuner are shown in the curves

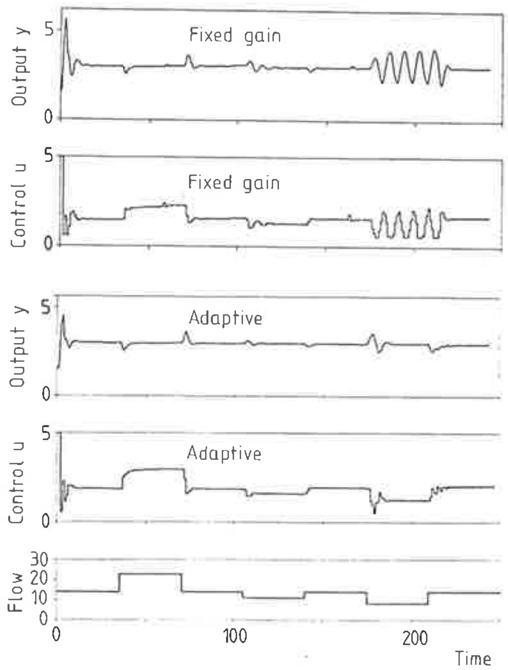

Fig. 5. - Results of experiments with varying flow. Results with a fixed gain regulator is shown in the curves labeled fixed gain. Results with an LQG self-tuner is shown in the curves labeled adaptive.

labeled adaptive in Fig. 5. The figure shows clearly that the self-turner can easily cope with the parameter variations. The parameters used in the self-tuner are $\varrho = 5$ and $\lambda = 0.98$. The sampling period is 15s.

Fig. 5 shows that the self-tuner has considerably better performance than a constant gain regulator. It is of course possible to make such a self-tuner unstable by decreasing the flow rate further.

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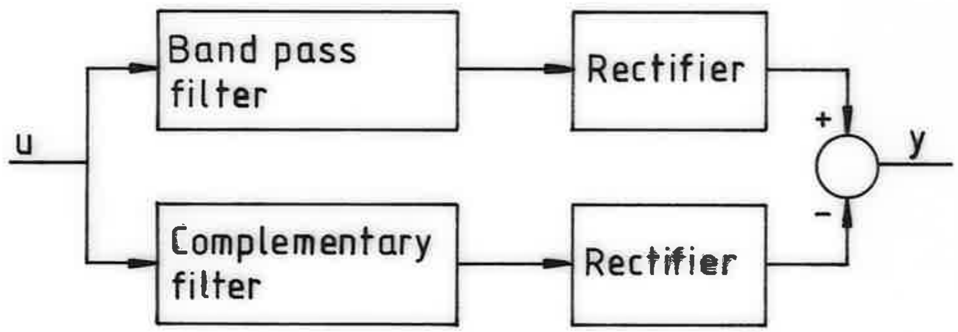
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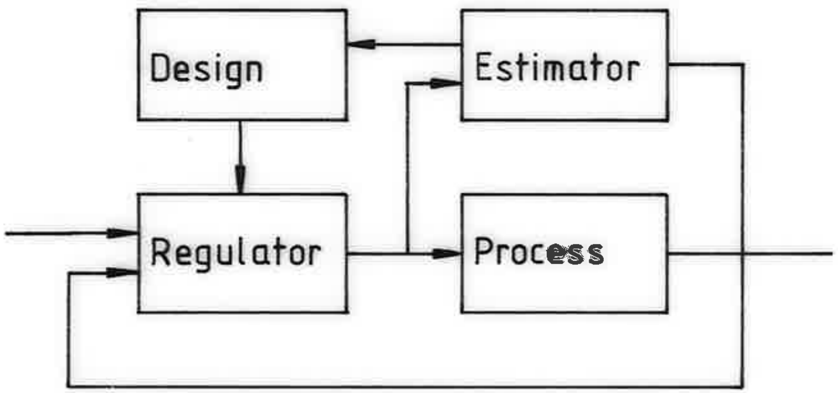
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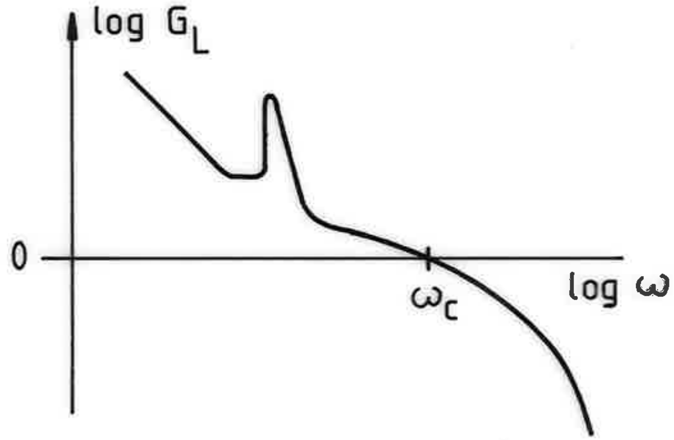
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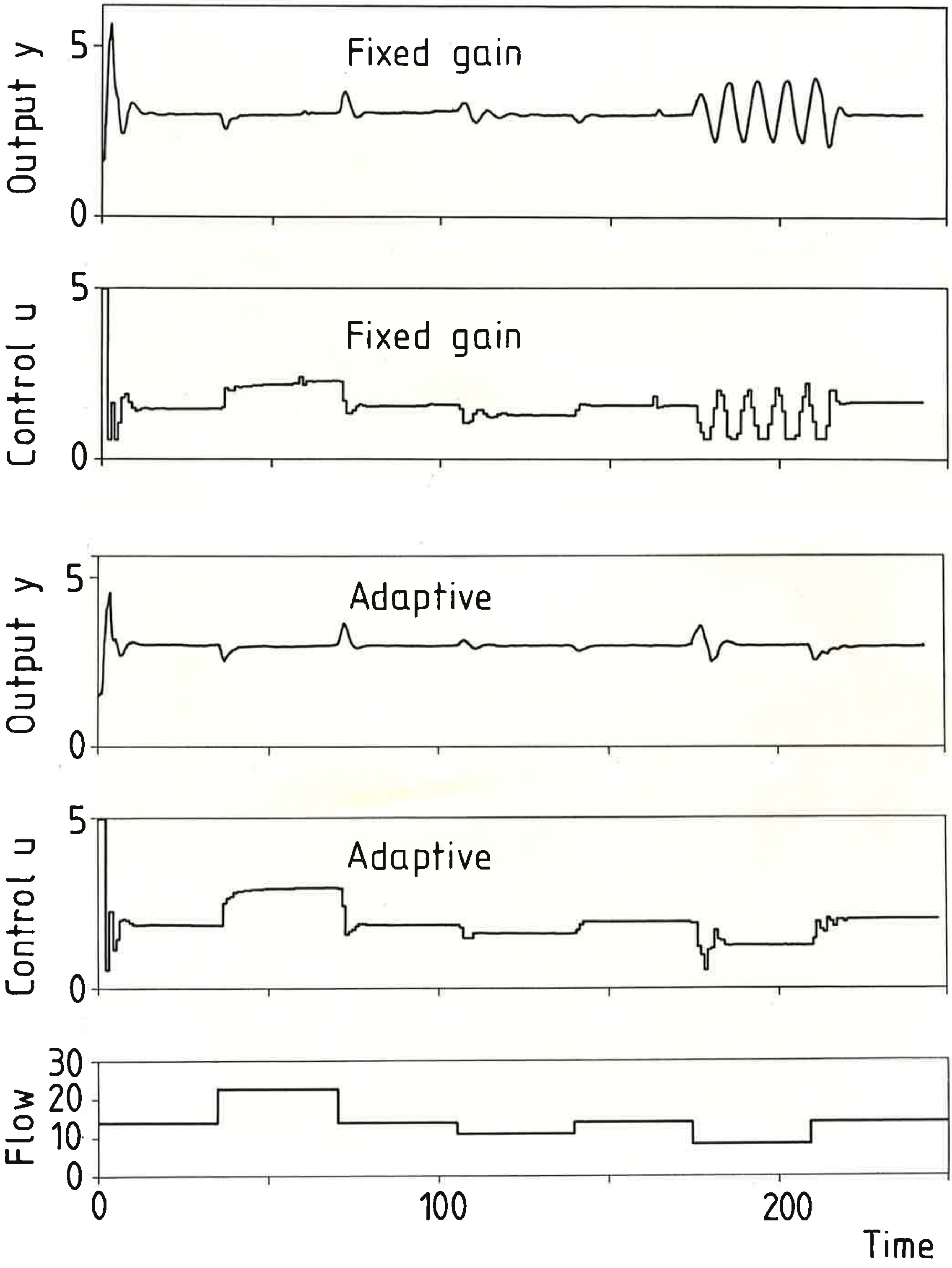

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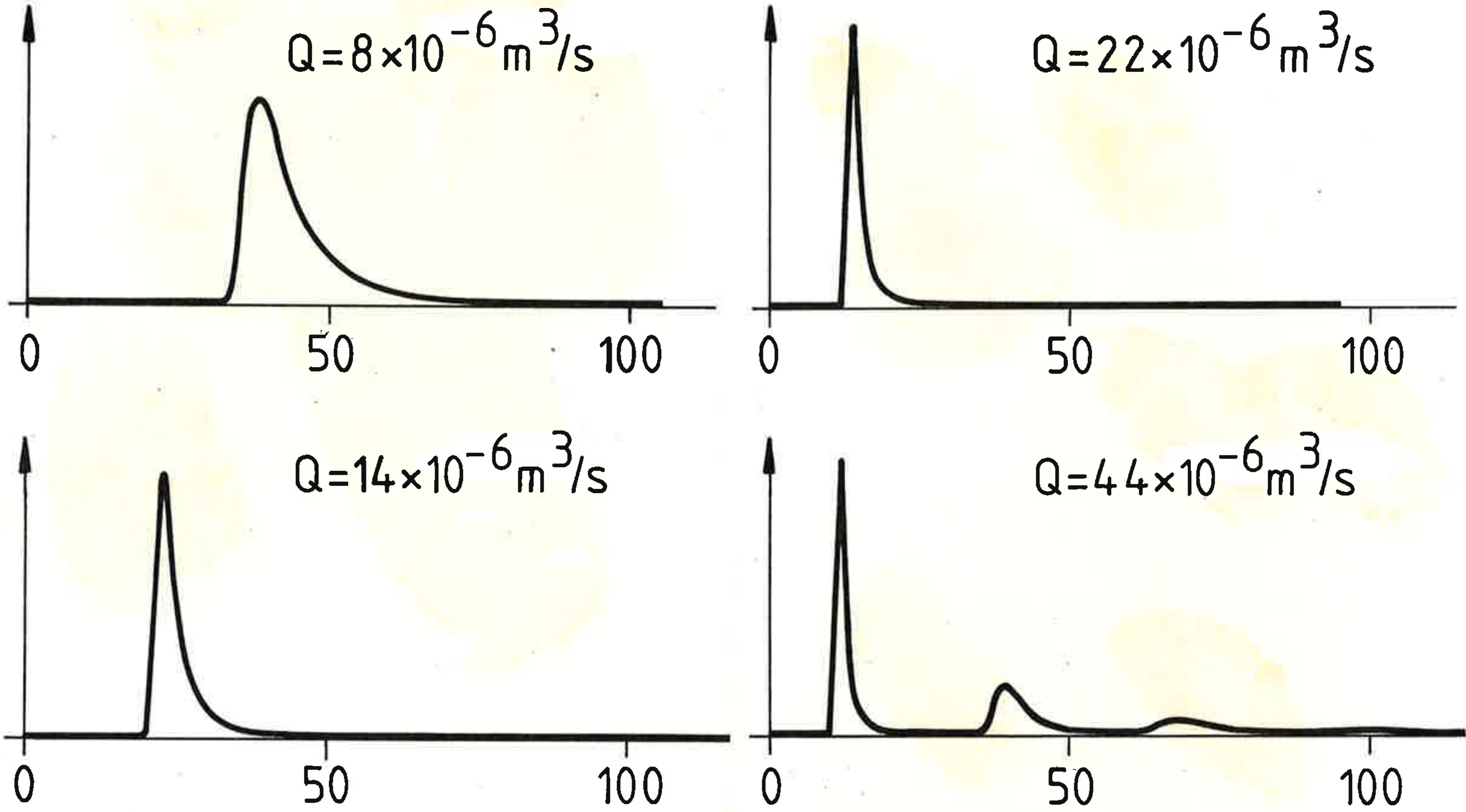

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