ADAPTIVE CONTROL OF CHEMICAL PROCESSES

Edited by

H. UNBEHAUEN

IFAC

ADAPTIVE CONTROL OF CHEMICAL PROCESSES

Proceedings of the IFAC Workshop, Frankfurt/Main
21–22 October 1985

Edited by

H. UNBEHAUEN
Automatic Control Laboratory, Ruhr-University, Bochum, FRG

Published for the

INTERNATIONAL FEDERATION OF AUTOMATIC CONTROL

by

PERGAMON PRESS

OXFORD · NEW YORK · BEIJING · FRANKFURT
SÃO PAULO · SYDNEY · TOKYO · TORONTO

U.K.	Pergamon Press, Headington Hill Hall, Oxford OX3 0BW, England
U.S.A.	Pergamon Press, Maxwell House, Fairview Park, Elmsford, New York 10523, U.S.A.
PEOPLE'S REPUBLIC OF CHINA	Pergamon Press, Qianmen Hotel, Beijing, People's Republic of China
FEDERAL REPUBLIC OF GERMANY	Pergamon Press, Hammerweg 6, D-6242 Kronberg, Federal Republic of Germany
BRAZIL	Pergamon Editora, Rua Eça de Queiros, 346, CEP 04011, São Paulo, Brazil
AUSTRALIA	Pergamon Press Australia, P.O. Box 544, Potts Point, N.S.W. 2011, Australia
JAPAN	Pergamon Press, 8th Floor, Matsuoka Central Building, 1-7-1 Nishishinjuku, Shinjuku-ku, Tokyo 160, Japan
CANADA	Pergamon Press Canada, Suite 104, 150 Consumers Road, Willowdale, Ontario M2J 1P9, Canada

First edition 1986

British Library Cataloguing in Publication Data

Adaptive control of chemical processes:
proceedings of the IFAC workshop,
Frankfurt/Main 21–22 October 1985.
1. Adaptive control systems
I. Unbehauen, H. II. International
Federation of Automatic Control
629.8'36 TJ217
ISBN 0-08-033431-8

Printed in Great Britain by A. Wheaton & Co. Ltd., Exeter

IFAC WORKSHOP ON ADAPTIVE CONTROL OF CHEMICAL PROCESSES

Organized by
VDI/VDE–Gesellschaft Mess–und Regelungstechnik, Düsseldorf, FRG

Sponsored by
International Federation of Automatic Control (IFAC)
Technical Committee on Applications
Technical Committee on Theory

Co-sponsored by
European Federation of Chemical Engineering
DECHEMA, Deutsche Gesellschaft für chemisches Apparatewesen eV

PREFACE

This volume contains the contributions presented at the IFAC-Workshop on "Adaptive Control of Chemical Processes" held in Frankfurt/Main during October 21/22, 1985. This workshop was the first devoted to the application of adaptive control in chemical industry. The high interest in this field was reflected by the number of about 130 participants mainly from industrial companies.

Although adaptive control strategies have been discussed broadly during the last 30 years it is only in the last few years that adaptive control has found real industrial applications. This situation is based on the one hand on the progress in the development of powerful adaptive control algorithms which have reached today a mature state. On the other hand, modern microelectronics offers cheap hardware which allows an easy realization of adaptive control strategies, leading already to commercially viable solutions.

Process control and especially chemical industry has become one of those fields, where adaptive control schemes have been introduced most widely and most successfully. A common property of these processes is that their dynamic characteristics alter during operation, so that an automatic adjustment of the controller parameters is necessary, in order to achieve good process operation over a wide range of conditions. Corresponding examples can be found in the broad field of applications included in the contributions of this workshop.

The aim of this workshop was to present and to discuss recent experiences and advances in the application of adaptive control in chemical and other related processes. About 70 papers had been invited or proposed from which finally 35 papers remained after a careful reviewing process through the members of the international programme committee. These papers had been presented in 8 lecture sessions and 3 poster sessions.

I hope that the results of this workshop will stimulate control engineers to apply adaptive control schemes still more to chemical processes.

H. Unbehauen
Editor

CONTENTS

DESIGN AND TESTING OF A NON-LINEAR ADAPTIVE CONTROLLER FOR A FLOCCULATION PROCESS

K. Ahrens

Dechema-Institut, Theodor-Heuss-Allee 25, D-6000 Frankfurt am Main 97, FRG

Abstract. A multivariable non-linear parameter-adaptive cascade controller for a semi-industrial flocculation plant is described. The static characteristics of the process are approximated by parabolas. The special multivariable problem is solved by a non-linear optimisation using the Lagrange multiplier method. To meet the special requirements due to the non-linear character of the system and the needs for practical application a multivariable testsignal has been designed. To increase the robustness on the one hand, the process identification is switched off after the initialisation of the controller, to conserve a minimum portion of adaptability on the other hand, a feedforward control feature has been installed to correct the gain of the master controller, using several disturbing variables as inputs. Theresults of some semi-industrial scale experiments based on real-world conditions are discussed.

Keywords. Adaptive control; cascade control; chemical variables control; feedforward; modelling; multivariable control systems; nonlinear control systems; optimisation; self-adjusting systems.

INTRODUCTION

Goal

Flocculation is an important step in the conversion of polluted surface waters to drinking water. Until now, such plants have been controlled only manually.

Just as with other industrial processes, too, automatic operation of flocculation plants should offer several advantages, e. g.:

- conserve as far as possible the desired product quality, i. e. the turbidity of the output water, by compensating for fluctuations of load or raw-water properties
- minimise the operating costs for a given quality, especially by savings in flocculant or polymers (flocculation aid)
- easy operation: Once the appropriate settings of the controller have been determined, the only input by the plant operator is the desired value of the product quality.

The research project , the results of which will be reported here, has been performed in cooperation with the Passavant-Werke, Aarbergen, FRG, a manufacturer of water treatment plants. The goals have been:

- the modification of an existing adaptive controller, developed and tested in laboratory environment by Ahrens (1983) ,
- the testing of a controlled semi-industrial plant under real-world conditions, using surface water from a river, and, finally,
- the estimation of the potential for industrial application.

Structural and Dynamical Properties

Figure 1 shows the semi-industrial plant used for the experiments. The process consists of two steps:

- generation of the flocs by chemical reactions in a cascade of four continuous stirred tank reactors
- separation of the flocs from the water using a parallel plate gravity separator which is combined with a sludge thickener.

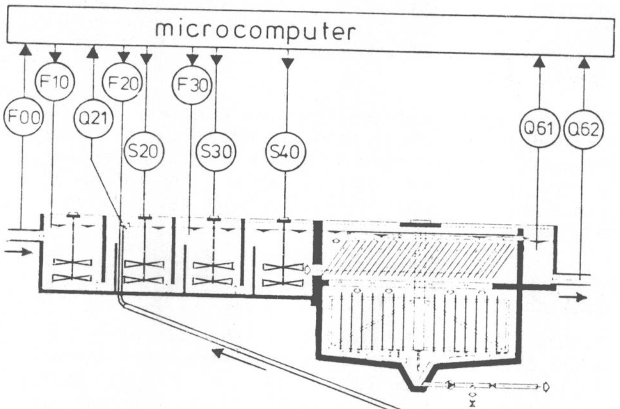

Fig. 1: Semi-industrial plant, schematic. Flow F00, density of contact sludge Q21, output turbidity Q61, pH-value Q62. Flocculant dose F10, contact sludge feed F20, polymer dose F30 (flocculation aid), stirring frequencies S20,...,S40. For the measured variables the arrow points into the microcomputer.

The controlled variable is the turbidity of the output water (Q61). The manipulated variables used for control are the flocculant dose F10, the contact sludge dose F20, the polymer dose F30 (flocculation aid), and the stirring frequency S30 in compartment three.

The input raw-water properties are unknown, slowly time-varying, and can only be detected from the behaviour of the plant output, see fig. 6.

The dependence of the output variable Q61 from the input variables can be described by non-linear static characteristics, see fig. 2, which show more or less significant minima, see Ahrens and Gundelach (1982). For small values of the manipulated variables, which is the important range for industrial applications, the shape of the characteristics can be approximated with sufficient accuracy by parabolas.

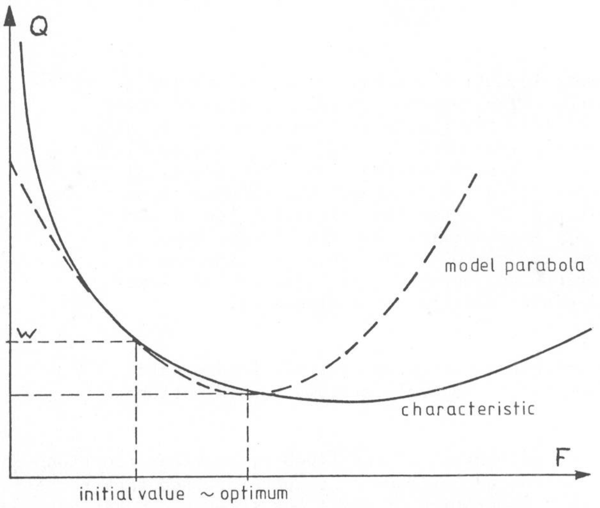

Fig. 2: Static characteristic, schematic: turbidity Q as a function of a manipulated variable F, e.g. the flocculant dose. Full line for the real shape, the parabolic approximation is dashed. The minimum of the parabola is an approximation for the technical optimum, i.e. the minimum turbidity. The initial value for F and the desired value w for the turbidity have to be input by the plant operator.

The mean residence time is approximately 20 min. The delay times range from 3 min to 10 min, the transient periods from 5 min to 10 min, depending on the particular input variable. The ratios of transient period to delay time are ca. 1.5 for all manipulated variables.

Concept

Figure 3 shows the concept of the controller.The controller is a simple cascade with a non-linear PI-master controller and a feedforward parameter-adaptive non-linear slave controller. The input variables of the master are the measured and desired values of the turbidity, the output is a particular value for the operating costs, which is fed into the slave controller as the reference variable.

To cover a wide range of loads, the sampling period is indirect proportional to the flow.

The output variables of the slave are the settings of those manipulated variables which have been elected for plant control. The slave can be regarded as a certain kind of ratio controller, eq. 16, where the mutual ratios depend on the model parameters and the specific costs associated with the manipulated variables. The ratios are determined using the method of the Langrange multipliers.

Experiments have shown that process excitation by the controller is unfavourable because the variations of the model input variables are not independent. Therefore a special testsignal and initialisation procedure have been designed.

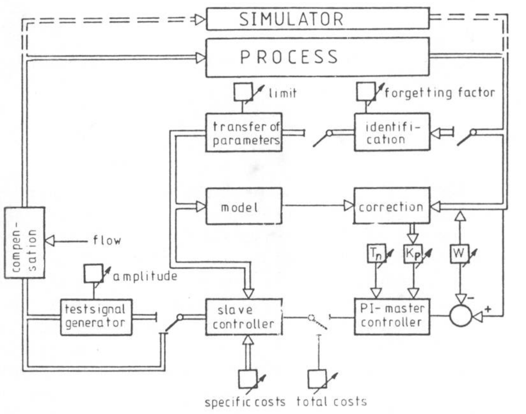

Fig. 3: Concept of the controller. For the testing of the software or methodological approaches the process is replaced by a simulator. For the setting of the controller only the gain K_p, the integration time T_n and the desired value w are required from the user.

Sometimes continuous process excitation by external testsignals is not feasible or excitation by the controller alone is not sufficient and can cause bad performance. Therefore the identification is switched off after the initialisation period. In order to provide adaptation to changing operation conditions and robust performance two additional feedforward features have been added to the controller. The first one is a convenient feedforward control with the load being the input, directly affecting the controller output. The second feature controls the gain of the master controller using the load, the desired value, the model error (as a measure for the disturbing variables other than load), and the specific costs.

DESIGN

Process Model

The dependence of the output variable x, the turbidity,from the various input variables y_i is described in terms of the following discrete nonlinear dynamical mathematical model of second order (Isermann, 1974; Lachmann and Goedecke, 1982). The ansatz takes into account the parabolic nature of the static characteristics and may be regarded as a simple phenomenological approximation for the mass balance of the chemical reactions representing the flocculation process, with the turbidity being a global measure for the concentrations of polluting substances:

$$x_k = -a_{10}x_{k-1} - a_{20}x_{k-2} + \sum_i (b_{i1}y_{ik-d_i-1} + b_{i2}y_{ik-d_i-2} + b'_{i1}y^2_{ik-d_i-1} + b'_{i2}y^2_{ik-d_i-2}) \quad (1)$$

The d_i are the deadtimes in units of the sampling period associated with the particular manipulated variables y_i. In contrast to models used with factorial designs no interactions, e.g. $x \cdot y_i$ or $y_i y_j$, $i \neq j$, are considered.

The bias, too, is not considered here. The bias may be regarded as a disturbing variable: A value different from zero means a shift of the static characteristics along the x-axis. The bias enters the controller via the ratio of predicted and measured output of the system, see eq. 9.

The contact sludge feeback line, see fig. 1, has not been included explicitely in the model because of the considerably low gain and the large mean residence time of the sludge in the thickener (the ratio of the flows F20 to F00 does not exceed 3%).

For the design of the controller the system has been decomposed into several SISO-subsystems with the manipulated variables y_i as input . The output variable x of the system has to be decomposed into contributions associated with the particular input variables of the total system to give the output variables of the subsystems, see Diekmann (1983). As the controller design , however, is based on simple feedforward controllers no information on the outputs of the subsystems is required, and it is sufficient to represent the subsystems by static models, the parameters of which can be calculated immediately from the model parameters of the total system:

$$b_i = \frac{b_{i1} + b_{i2}}{1 + a_{10} + a_{20}} \qquad (2)$$

$$b'_i = \frac{b'_{i1} + b'_{i2}}{1 + a_{10} + a_{20}} \qquad (3)$$

Using feedback controllers would have resulted in a much more complicated solution, see Ahrens (1983), than has been found here. The parabola in Fig. 2 is a typical example of a static model for a subsystem.
If, however, severe requirements exist concerning the dynamical properties of the controller the modelling approach described here has to be used with care.

Equations 1,2,3 give the static model for the total system:

$$x = \sum_i (b_i y_i + b'_i y_i^2) \qquad (4)$$

The technical optimum can be approximated by the minima of the model parabolas with the coordinates $\bar{y}_i$ and $\bar{x}_i$:

$$\bar{y}_i = -\frac{b_i}{2b'_i} \qquad (5)$$

$$\bar{x}_i = -\frac{b_i^2}{4b'_i} \qquad (6)$$

with the turbidity minimum x_{min} being:

$$x_{min} = \sum_i \bar{x}_i \qquad (7)$$

Identification

Prefiltering. Because of the poor signal to noise ratio the following filter for the process data has been used: The five latest sets of process data are grouped together. With the two oldest sets a linear forward extrapolation of the system output is performed and a linear backward extrapolation is done with the two latest sets. The measured output obtained two sampling periods ago can be limited by the extrapolations as upper and lower bounds.

The deadtime introduced by this method is negligible if compared with the mean residence time of the process data in the memory of the identification algorithm. Of course this filter introduces an additional error, if the process output is changing very rapidly.

Method. The model parameters are calculated from the process data using a least squares method. The matrix of the system of linear equations is updated continuously by the latest process data using a forgetting factor λ , which depends on the mean residence time τ of the process data in the memory of the algorithm according to eq. 1:

$$\lambda = \frac{1}{1 - \tau} \qquad (8)$$

The experiments have shown that τ should not be smaller than 50 sampling intervals. Optimum performance is achieved at around 200 sampling intervals or more. Large values of τ mean high stability of the algorithm.

Infinite τ can be obtained simply by interrupting the connection between data acquisition and identification algorithm, see fig. 3.

Corrections. The fact that the static characteristics always have positive curvature can be employed to correct the model parameters b_i', see eq. 3.

A Negative value for one of these parameters would lead to instabilities in the control algorithm, as the minimum of the associated characteristic would be converted to a maximum and the according manipulated variable would be set close to the lowest possible value because the minimum turbidity would be expected there.

Appropriate values for the lower bounds of the curvature can be estimated from the signal to noise ratio of the turbidity sensor and the ranges of operation of the particular manipulated variables. The Experiments have shown that the correction algorithm for the model parameters is active only in the case of static characteristics with considerably low curvature.

Process Excitation

For the design of the testsignal the multivariable character and the nonlinearities of the process have been taken into account, exceeding the convenient requirements concerning amplitude, frequency and bandwidth, see e.g. Grisse (1983). Because of the time-varying operating conditions the testsignal cycle period should be as short as possible.

In fig. 4 the time dependence of the manipulated variables has been depicted for one cycle of the testsignal, taking approximately 100 sampling intervals, which is at the same time the minimum value for one cycle if four manipulated variables are involved.

Each manipulated variable contributes to the test signal a sequence of rectangular pulses, the widths being directly proportional to the particular transient periods. The pulsewidths can be estimated from the geometrical plant properties with sufficient accuracy. To minimise the number of sampling intervals required for one cycle the bandwidth is as small as possible ("monochromatic" pulses).

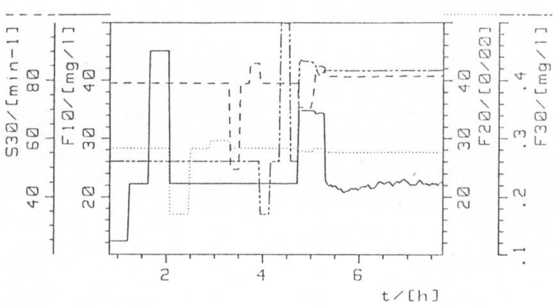

fig. 4: Computer simulation of the testsignal for the initialisation of the controller, see the real experiment in fig. 5.

In contrary to the convenient PRBS-design three instead of only two different settings of the input variables had to be included to obtain the additional information required for the determination of the curvature. Process simulations favoured the arrangement of the three different settings in the order of increasing values. The three amplitudes are not equally spaced to compensate for the nonsymmetric shape of the static characteristics. The medium amplitude is the starting value suggested by the plant operator. To save time only one of the two possible different sequences has been included. The testsignal is deterministic.

As there are no interaction terms, the model does not require simultaneous excitation by two or more variables, see eq. 1. Experiments, too, have shown that simultaneous excitation causes unfavourable results. So only one manipulated variable varies at a time.

Controller

Master controller. For the master controller a non-adaptive design has been chosen because of the limited RAM-capacity of the eight bit microcomputer used for the control of the semi-industrial plant.

For a P-controller as master controller only considerably low gains were feasible because of the relatively large deadtime of the process. Consequently a simple proportional controller would produce a large permanent control deviation. Therefore an integral part has been introduced. To prevent controller wind up the integral part is limited to the range from 0 % to 100 % of the costs resulting for operation at the technical optimum, which is determined by the parameters of the nonlinear model, eqs. 5 and 6.

To compensate for the non-linear dependence of the turbidity from the operating costs, which can be assumed of similar shape as the static characteristic in fig. 2, the controller output is the reciprocal value of a conventional PI-controller.

With the gain K_p and the integration time T_n being preset properly a feedforward control feature, see fig. 3, corrects the controller gain for changes in load F00 or changes of the desired value w of the turbidity or deviations of the model output $\hat{x}$ from the measured value x (which are assumed to be due to changes of unknown or non-measurable disturbing variables), or changes in the specific costs $\varkappa_i$ associated with the manipulated variables. Empirical reasoning has resulted in the following ansatz:

$$K_p = \left(\frac{F00}{F_o}\right)^2 \left(\frac{w_o}{w}\right)^2 \left(\frac{x}{\hat{x}}\right) \left(\sum_i \varkappa_i \sum_i \frac{1}{\varkappa_i}\right)^{1/2} \qquad (9)$$

(w_o and F_o are the starting values for w and F00) It has been assumed that the controller gain should be indirect proportional to the slopes of the static characteristics at the controller set point. The slopes usually decrease if the load or other disturbing variables increase or if the desired value is reduced. The last factor can be made plausible using eq. 12. The exponents 1/2, 1 or 2 have been determined from process simulations.

Slave controller. The multivariable problem is solved by a non-linear optimisation using Lagrange multipliers. The manipulated variables y_i are calculated for maximum product quality, i. e. the turbidity is a minimum for the total costs K_o supplied from the master controller.

$$K = \sum_i \varkappa_i y_i = \text{const.} = K_o \qquad (10)$$

The minimum condition is:

$$x + \gamma (K - K_o) \longrightarrow \min \qquad (11)$$

which can be transformed into the control law using eqs. 4, 10, and 11:

$$y_i = -\gamma \frac{\varkappa_i}{2b_i'} - \frac{b_i}{2b_i'} \qquad (12)$$

where the Lagrange multiplier γ is:

$$\gamma = (K_{opt} - K_o) / \sum_i \frac{\varkappa_i^2}{2b_i'} \qquad (13)$$

K_{opt} are the costs resulting for operation at the technical optimum:

$$K_{opt} = -\sum_i \varkappa_i \frac{b_i}{2b_i'} \qquad (14)$$

Using eq. 5 , from eq. 12 the distance from the minimum of the according model parabola of the settings for the manipulated variables Δ_i can be calculated:

$$\Delta_i = y_i + \frac{b_i}{2b'_i} = - \frac{\varkappa_i}{2b'_i} \quad (15)$$

Consequently the slave controller operation can be interpreted as that of a ratio controller, where the mutual ratios of the Δ_i are directly proportional to the ratio of the specific costs $\varkappa_i$ and indirect proportional to the ratio of the curvatures b'_i :

$$\Delta_i / \Delta_j = \frac{\varkappa_i}{\varkappa_j} \cdot \frac{b'_j}{b'_i} \quad (16)$$

TESTING

Initialisation

The initialisation procedure for the controller immediately follows the conventional start-up of the plant. This procedure can be subdivided into three steps :

- The first step is excitation of the process for some hours with the specially designed testsignal, see fig. 4, sampling of the process data, and calculating finally the first, still preliminary values for the model parameters, see fig. 5, t=0 ... 3.6 h.

- The next step is using the model parameters for approaching the turbidity minimum while the parameters are fed back to the controller and recalculated continuously, thus achieving corrections by evaluating the transition to the technical optimum, see fig. 5, t=3.6 ... 4.2 h, the turbidity decreases significantly from 0.8 TE/F to 0.3 TE/F.

- The last step is switching off the parameter estimation, and transition to the normal mode of operation at the desired value for the turbidity, 0.8 TE/F in fig. 5. The transient behaviour of the controlled plant can be used to manually correct the settings of gain and integration time for the master controller.

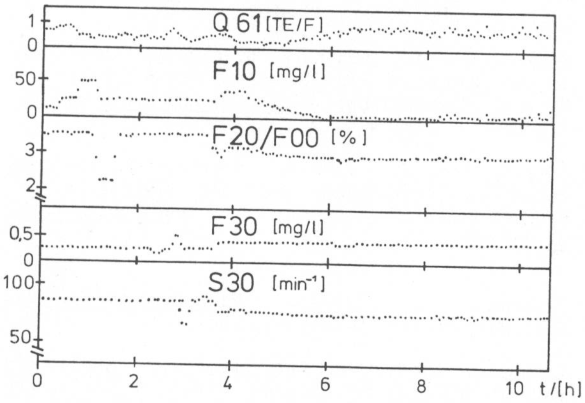

fig. 5: Initialisation procedure, experiment: excitation by testsignals, optimisation and identification. Interrupting the identification and transition to normal operation.

Process simulations show that for reasonable amplitudes of the testsignal the signal to noise ratio of the turbidity signal as well as different starting values for the manipulated variables do not influence the results significantly. For the setting of the master controller gain, however, it makes a difference if the raw-water quality is better or if it is worse than usual.

Performance

Normal operation. The behaviour of the controlled plant under natural changes of the disturbing variables can be seen in fig. 6. Although the raw-water quality gradually decreases, the turbidity is constant. If the raw-water quality increases, the demand for flocculant, which is the most expensive manipulated variable , decreases significantly, allowing for considerable savings.

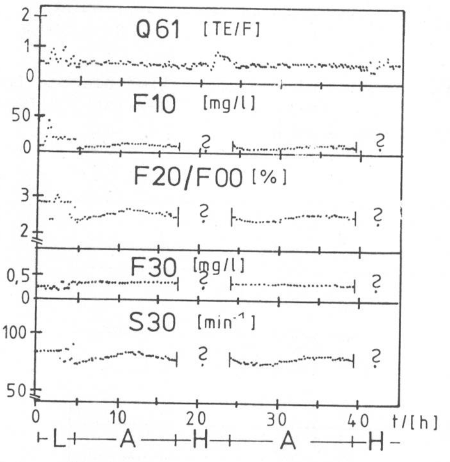

fig. 6: Normal operation of the semi-industrial plant. The initialisation (L) is followed by automatic operation (A), which is interrupted by manual operation (H) during the day.

If the desired value for the turbidity is less than that one achievable at the most favourable operation conditions, then, however, the manipulated variables will always be set to the minima of the model parabolas (technical optimum), and there will obviously be no difference to manual operation.

Variation of load. In fig. 7 the flow changes stepwise between 7 m3/h and ca. 9 m3/h. Convenient feedforward control of the load alone is not able to keep up the desired quality. The expensive flocculant dose changes by a factor of four, while the other manipulated variables, which are considerably cheaper, keep close to the minima of the model parabolas.

Variation of raw-water properties. In contrary to the measurable changes in load there is no possibility to employ feedforward control using the raw-water properties. Therefore the performance of the controlled plant in fig. 8 is considerably poorer than in fig. 7. After switching on the pump for the dosing of polluting substances the turbidity exceeds the value of 1 TE/F for ca. 35 min. To estimate the practical applicability, however, one should bear in mind, that the change of the disturbing variable performed here in the experiment is very much faster than will probably be the case in any practical application, compare e. g. fig. 6.

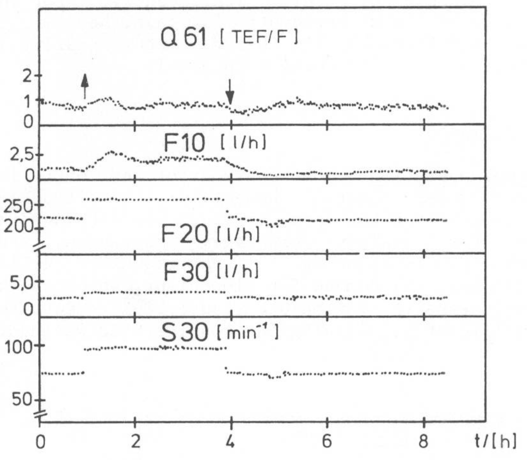

fig. 7: Performance of the controlled plant after changes in flow (arrows). Stepwise changes between 7 m3/h and 9 m3/h.

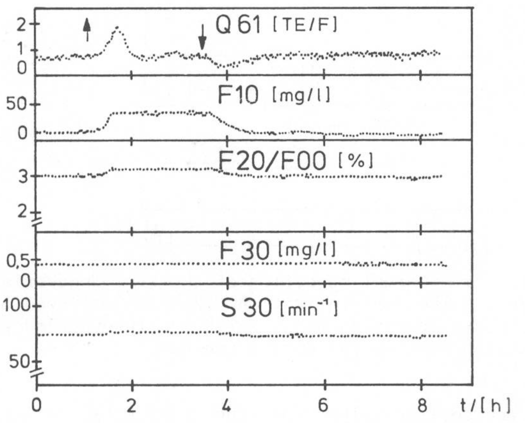

Fig. 8: Performance of the controlled plant after switching (arrows) a dosing pump for polluting substances, which affect the flocculation reactions. The performance in fig. 7 is better, because the flow is measurable, whereas the effect of the polluting substances has to be detected from the plant output.

Process simulations have shown that the performance of the controlled plant after changes of the raw-water properties can be improved considerably by

- operating at lower desired values for the turbidity or
- by deviating from the real specific costs , in order to raise the flocculant dose, see eq. 16, for better compensation of the disturbing variables at the plant input.

CONCLUSION

As far as the treatment of surface waters is concerned, the experiments have shown adequate performance of the controlled plant under the assumption that the product quality is strongly correlated with the turbidity.

As for the estimation of the product quality, however, the results of mostly time-consuming or laborious off-line chemical analyses in the plant laboratory are decisive , the on-line turbidity signal can only be a global indicator for the product quality . If the laboratory quality is not sufficient at the desired turbidity set point, it can be improved by changing the ratios in eq. 16, if the laboratory quality is sensitive towards the ratios. In this case the specific costs have to be altered and the optimisation of the operating costs is no longer straight-forward. If suitable analytical sensors for particular aspects of the product quality are available the ratios can be tuned automatically by introducing additional control loops.

To improve the performance after changes of the raw-water properties, see fig. 8, analytical sensors, such as the one developed by Eisenlauer and Horn (1985), can be used for feedforward control of one suitable manipulated variable,e.g. the flocculant, especially for plants with considerable mean residence times.

ACKNOWLEDGEMENTS

The author is indebted to Mr. Berlenbach, Klegraf, and Geyer, Passavant-Werke, Aarbergen, FRG, and Dr.von Hagel, sometime Passavant-Werke, for the harmonic cooperation, and to the Federal Minister for Research and Technology for financially supporting the project "Qualitätssteuerung der Trinkwasserflockung mittels EDV" by the Projektträger Wassertechnologie at the Kernforschungszentrum Karlsruhe, FRG.

REFERENCES

Ahrens, K., and V. G. Gundelach (1982). Überwachung der Flockung mit Hilfe eines rechnergesteuerten physikalischen Modells. gwf-wasser/abwasser, 123, 131-138.

Ahrens, K. (1983). Adaptive Regelung für ein Trinkwasserflockungsverfahren. Lecture delivered at Dechema-Jahrestagung 1983, accepted for publication in automatisierungstechnik(at).

Diekmann, K. (1983). Identifikation von Mehrgrößensystemen. Teil 1: Modellbildung. Teil 2: Parameterschätzverfahren und spezielle Probleme der Mehrgrößenidentifikation. regelungstechnik (rt), 31, 355-361 and 398-402.

Eisenlauer, J. ,and Horn, D. (1985). Fibre-Optic Sensor Technique for Flocculant Dose Control in Flowing Suspensions. Colloids and Surfaces, 14, 121-134.

Grisse, H. J. (1983). Über den Einfluß des anregenden Testsignals auf die Ergebnisse von Parameterschätzverfahren. regelungstechnik, 31,361-368.

Isermann, R. (1974). Prozeßidentifikation. Springer, Berlin, Heidelberg, New York.

Lachmann, K.-H., and Goedecke, W. (1982). Ein parameteradaptiver Regler für nichtlineare Prozesse. regelungstechnik (rt), 30, 197-206.

INTEGRAL ACTION AND MODE TRANSITIONS IN SELF-TUNING PROCESS CONTROL

L. Rundqwist

Department of Automatic Control, Lund Institute of Technology, PO Box 118, S-221 00 Lund, Sweden

ABSTRACT

This paper focuses on two issues in self-tuning control, integral action and integral windup. Particular attention is given to the problems arising when self-tuning controllers are cascaded with other controllers. When control loops are coupled via utilization of a flow from a common source, the coupling may increase these problems.

INTRODUCTION

The process configuration discussed in this paper was encountered in an activated sludge system in a waste-water treatment plant, with parallel almost identical processes for degradation of biological waste. The processes are oxygenized by air flows, see Fig 1. The air production system has a number of compressors, which supply all processes. The processes have individual air flow rate controllers, which will interact when air flows are changed. The set point is given by another (possibly self-tuning) controller, see Fig. 2. The maximum available air flow to each process is time-varying.

The air flow supply is a common control problem, see Shinskey (1978). The header pressure is controlled (by PC). The pressure set point is either constant or computed by a valve position controller (VPC), that will make the most-open control valve almost wide-open, see Fig. 3. Then at least one control valve operates close to saturation, and the air flow is produced at lower power demand. This type of process arrangement may be usual in process industry. The flow may be any gas or liquid, which is supplied to multiple users from one production unit.

The characteristic features of this control problem are varying process dynamics, load disturbances and saturations with varying limits. Windup in the cascaded self-tuning controller is analysed. A few antiwindup solutions will be given. Results from the implementation of self-tuning dissolved oxygen control in a wastewater treatment plant will be given.

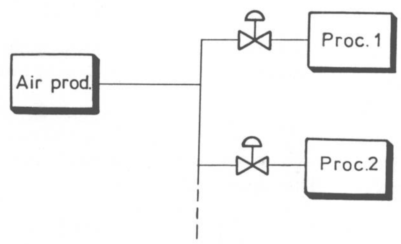

Fig 1 Process configuration.

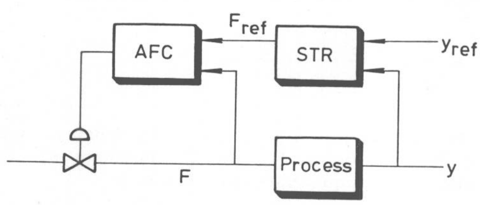

Fig 2 Air flow rate control and self-tuning process control.

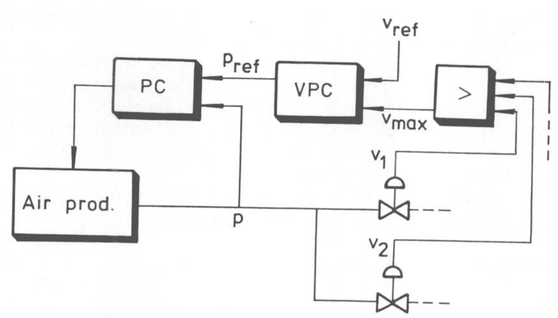

Fig 3 Pressure control and valve position control.

INTEGRAL ACTION IN SELF-TUNING CONTROLLERS

This section considers integral action in implicit self-tuning controllers with least squares estimation, see Åström (1983). The subject has been studied by several authors. Here, the approach is mainly to study the underlying design equation for minimum variance control of known time-invariant systems. It is assumed that if the forgetting factor $\lambda = 1$ and the parameters converge, they converge to the solution of the design equation.

If the forgetting factor $\lambda < 1$, the parameters are assumed to converge to a neighbourhood of the solution. If the process is time-varying, then λ must be less than one, else the controller is unable to track parameter variations. In Examples 1 and 2 below, the output variance of the closed loop as a function of controller parameters will be used to show that the parameters approach the solution of the design equation.

In a non-integrating control law the adaptation mechanism itself provides integral action. Using the R, S, T - notation for the controller, it was noted in Wittenmark and Åström (1984) that the covariance conditions for inputs and outputs are valid only if $\hat{R}(1) = 0$, when the process has a load disturbance. If $\hat{R}$ has only one parameter the output deterioration may be severe, see Example 1 below.

Several methods to achieve integral action in self-tuning controllers can be found in the literature, e.g. in Åström (1980), Allidina and Hughes (1982), Wittenmark and Åström (1984), and Tuffs and Clarke (1985). In Tuffs and Clarke (1985), the following controller structure can be found.

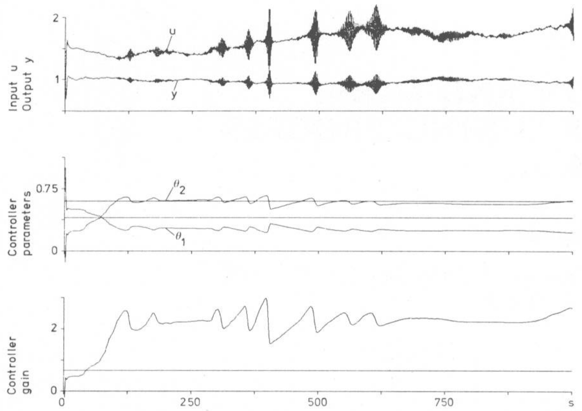

Fig 4 Non-integrating control (6a) of the process in Example 1.

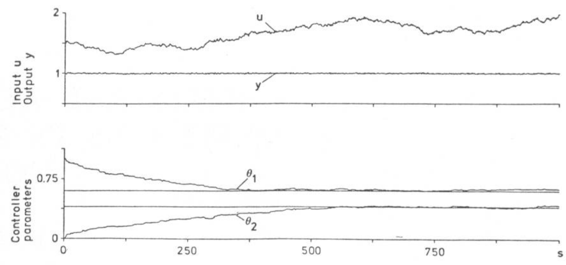

Fig 5 Integrating control (6b) of the process in Example 1.

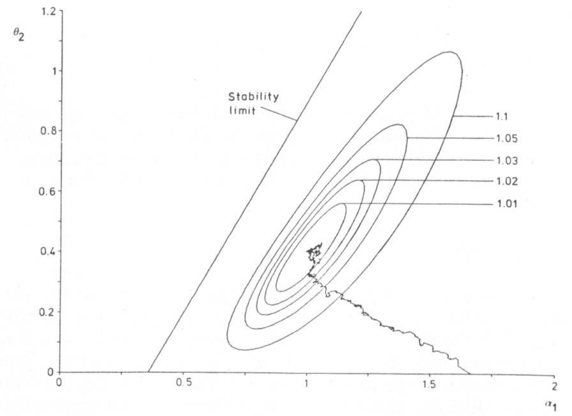

Fig 6 Contour levels for (8) and parameter estimates from Fig 5.

The process model is

$$A(q^{-1})y(t) = q^{-d}B(q^{-1})u(t) + \frac{C(q^{-1})}{1 - q^{-1}} e(t) \qquad (1)$$

i.e. the load is filtered, integrated white noise. B is stable. Tuffs and Clarke treat the case C = 1, but here a general C will be used.

To achieve integral action, R is factored into $R'\cdot\Delta$, where $\Delta = 1 - q^{-1}$. Further S is here chosen as $S = T(1) + S'\cdot\Delta$. T is a known polynomial and u_c the reference value. The controller is then

$$T u_c(t) = R'\Delta u(t) + [T(1) + S'\Delta] y(t) \qquad (2)$$

where $R' = R_1B$. R' and S' are to be estimated in the adaptive case. Then the closed loop is given by

$$y(t) = \frac{q^{-d}T u_c(t) + R_1e(t)}{AR_1\Delta + q^{-d}(T(1) + S'\Delta)} \qquad (3)$$

In stationarity, q = 1, the gain from u_c will be unity, irrespective of R_1 and S'. Further, the design equation for minimum variance control is

$$AR_1\Delta + q^{-d}(T(1)+S'\Delta) = C \qquad (4)$$

which can be solved for unique R_1 and S' if $\deg(R_1) = d-1$, $\deg(S') = \deg(A)-1$, and $T(1) = C(1)$.

To obtain a minimum variance controller $T(q^{-1})$ should be chosen as $C(q^{-1})$, which is unknown in the adaptive case. Then, for almost any choice, $T(1) \neq C(1)$, and (4) cannot be solved. Still the self-tuning controller may converge to the minimum variance solution, the reference value being mean value.

If αR_1 and $\alpha S'$, $\alpha > 0$, are substituted for R_1 and S' in (2), the MV design equation becomes

$$\alpha AR_1\Delta + q^{-d}(T(1)+\alpha S'\Delta) = \alpha C \qquad (5)$$

which can be solved if $\alpha = T(1)/C(1)$. Then the stationary gain from u_c is still unity. In the adaptive case, $\hat{R}'$ and $\hat{S}'$ will simply approach αR_1B and $\alpha S'$, respectively.

Thus a self-tuning controller based on this algorithm will always have unit stationary gain from reference input, and may approach the minimum variance solution.

Example 1: This example compares integrating and non-integrating implicit self-tuning control of a first order system given by $A = 1-0.4q^{-1}$, $B = 0.6$, $C = 1$, and $d = 1$ in (1). The noise variance is $\sigma^2 = 10^{-4}$. With the exception of C, this process model and the same noise sequence will be used in all examples throughout the paper.

Choose T = 1. Then the non-integrating controller is

$$\hat\theta_1 u(t) = u_c(t) - \hat\theta_2 y(t) \qquad (6a)$$

and the integrating controller is

$$\hat\theta_1 \Delta u(t) = u_c(t) - y(t) - \hat\theta_2 \Delta y(t) \qquad (6b)$$

(6a) is the controller to be used if the process has no load disturbance, but in this case its performance is bad. Using (6a) the closed loop is given by

$$y = \frac{q^{-1}}{A\hat\theta_1 + q^{-1}\hat\theta_2} u_c + \frac{\hat\theta_1}{A\hat\theta_1 + q^{-1}\hat\theta_2} \frac{1}{1-q^{-1}} e \qquad (7)$$

This structure cannot cancel the integrator, and will thus (for constant parameters) have infinite variance. The only way for the self-tuning controller to eliminate the noise is letting $\hat\theta_1 \rightarrow 0$, which will give infinite gain in the controller.

In Fig. 4 a simulation of this case with forgetting factor $\lambda = 0.998$ is shown. As can be seen, the gain increases (above the 'stability limit') until good identification is obtained. Then the gain is reduced and the procedure is repeated.

In Fig. 5 the same process is controlled by (6b), using $\lambda = 0.998$ with good performance. The output variance (with $\sigma^2 = 1$, a = 0.4) as a function of $\alpha_1 = \theta_1/0.6$ and θ_2 is

$$V = \frac{\alpha_1^2[\theta_2 - a\alpha_1 - \alpha_1]}{[\theta_2 - a\alpha_1 + \alpha_1][2\theta_2 - 2a\alpha_1 - 2\alpha_1 + 1]} \qquad (8)$$

Contour levels and the parameter estimates from Fig. 5 are shown in Fig. 6. As is easily seen, the parameters approach the solution of the design equation. □

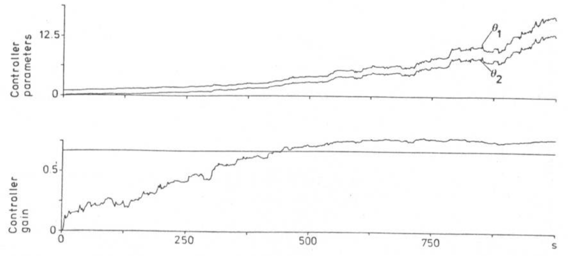

Fig 7 Integrating controller on process without load disturbance. Only gain and parameters are shown.

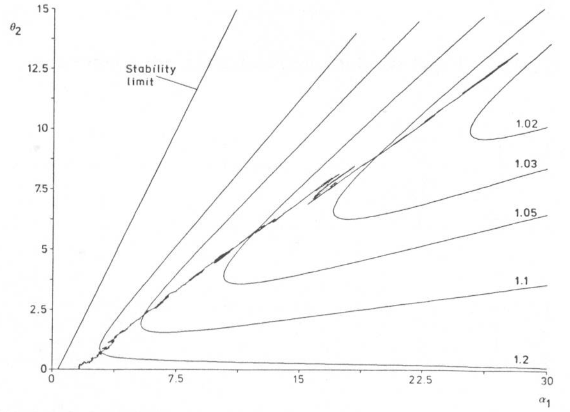

Fig 8 Contour levels for (10) and parameter estimates from Fig 7.

If, on the other hand, the integrating controller (2) is used on a process without load disturbance, there may be another type of deterioration. This case corresponds to letting $C = C'\cdot\Delta$ in (1), i.e. cancelling the integrator. Then $C(1) = 0$, which implies that the scale factor α must be infinite, else there is no solution to (5). In the limit ($\alpha = \infty$), (5) turns into

$$AR_1 + q^{-d}S' = C' \tag{9}$$

i.e. the design equation for minimum variance control of a process without load disturbance. The estimated parameters $\hat{R}'$ and $\hat{S}'$ will grow towards $\alpha R_1 B$ and $\alpha S'$, where α is large and R_1 and S' are given by (9).

Thus this algorithm is able to eliminate the integral action if it isn't necessary. This may cause problems if a load is switched on and off, and it is off for a long period, see Example 2.

Example 2: A, B, d and σ^2 is the same as in Example 1. $C = \Delta$, i.e. the disturbance is pure white noise. First, in Fig. 7, it is shown that the parameters drift away (towards infinity) when (6b) is used, but the gain $\hat{\theta}_2/\hat{\theta}_1$ is bounded. This can also be seen in Fig. 8, where contour levels for the closed loop output variance as a function of $\alpha_1 = \theta_1/0.6$ and θ_2 are shown together with the parameter estimates from Fig. 7. The variance ($\sigma^2 = 1$ and $a = 0.4$) is given by

$$V = \frac{-2\alpha_1^2}{\left(\theta_2 - a\alpha_1 + \alpha_1\right)\left(2\theta_2 - 2a\alpha_1 - 2\alpha_1 + 1\right)} \tag{10}$$

which has no local minimum in the stable area. Further (10) can be compared with the output variance when using the non-integrating controller (6a) instead.

$$V = \frac{-\alpha_1^2}{\left(\theta_2 - a\alpha_1 + \alpha_1\right)\left(\theta_2 - a\alpha_1 - \alpha_1\right)} \tag{11}$$

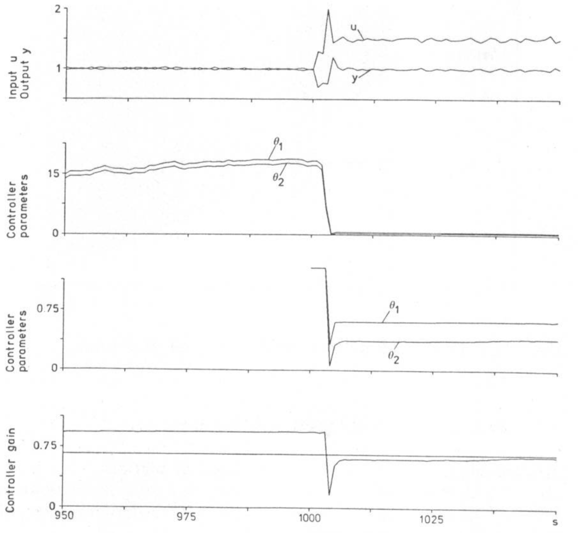

Fig 9 A constant load is added, continuation from Fig. 7.

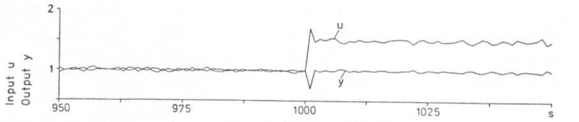

Fig 10 Constant integrating controller.

When the parameters in (10) grow large then (10) is approximately equal to (11). (11) is a function of θ_2/α_1 only. Thus only the gain is required to converge. □

Example 3: In Fig. 9, a constant load is introduced, when the parameters are large. The disturbance is then a constant load and white noise. In Fig. 10 a comparison with a constant gain integrating controller is done. The conclusion is that integral action is lost for a few samples in Fig. 9. Before the load change it is minimum variance control in Fig 9, but not in Fig 10. □

INTEGRAL ACTION IN CASCADED SELF-TUNING CONTROLLERS

Using a self-tuning controller cascaded with another controller, see Fig. 2, creates special problems during saturation conditions. Saturation in the control output of the self-tuner is more easily taken care of (internally in the algorithm), see Wittenmark and Åström (1984), but when the cascaded controller saturates, this information must be fed back to the self tuner. Otherwise it will give two types of windup, control output windup due to integral action, and parameter windup, if the estimation continues.

The process configuration considered, see Fig. 1-3, enhances the saturation problem, since (at least) one throttle valve operates close to saturation. The actual upper limit for the control output from the self-tuner is time-varying and unknown.

In Fig. 11 it is shown what a saturation may look like, when the available control authority decreases. The thick line (u) is the continuous time control input to the process, and u_{ref} is the output from the self-tuner. In the subsequent examples, this type of saturation will be studied.

The means to be used to handle windup problems are different limits for the control output, and that the controller could be run in different modes. In the sequel the controller will have absolute and rate limits for the control output. Automatic mode and estimation can be switched on and off independently, and an external control signal is output in manual mode.

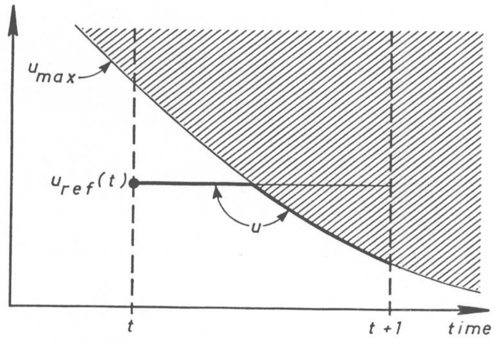

Fig 11 Continuous time control signal and limit.

The following notation will be used.

Analog signals		Logical signals	
HI	Upper limit	AUTO	Automatic/manual
LO	Lower limit	ADAPT	Adaptation on/off
DH	Positive rate limit		
DL	Negative rate limit		
UEXT	External control signal		

In addition to the process output y(t), the following signals are available to the controller. The measured control input $u_m(t)$, the valve position v(t), which is a nonlinear function of $u_m(t)$, and logical signals indicating saturation of the valve. These signals can be used by the controller to compute limits, switch off estimation etc, thus avoiding windup.

In the simulations both process and controller are in discrete time. Special care is then taken to account for the effect of the saturation of u(t).

In Example 4 below, the two types of windup will be demonstrated. A few attempts to avoid windup will be described in Examples 5-9. A Pascal-like notation will be used, where HIGH indicates upper saturation of the valve, and LOW lower saturation.

In these Examples, the process in Example 1, controller (6b) and the saturation is used. The set point for the self-tuner is 1. The lower limit for the control value is 0, and the upper limit u_{max} is 2, except for the interval [50,100], where it is given by

$$u_{max}(t) = 2 + \sin\left(\frac{2\pi t}{100}\right) \tag{12}$$

The controller uses the limits 0 and 2, unless anything else is said.

Example 4: No information on saturations is used in this example. In Fig 12-13 both reset windup and parameter windup is shown. The reset windup for constant parameters in Fig 12 is quite large, but the estimation using false data makes the situation in Fig 13 much worse. □

Example 5: The rate limit is zeroed when the limit is hit. Further, the parameter estimation is stopped, i.e.

if HIGH then DH=0, ADAPT=0;
if LOW then DL=0, ADAPT=0;

The result can be seen in Fig 14. The control output u_{ref} is constant during the period. At the end of the limit period, a small reset windup can be seen in the process output, because the load is slightly smaller at the end of the period. If the load is larger at the end, it simply takes longer time before the output is normal, but there is no windup. □

Example 6: Here the absolute limits are given the same value as the measured control input u_m and the estimation is switched off at saturation. The estimation and the full control space is used immediately when the valve is unsaturated, i.e.

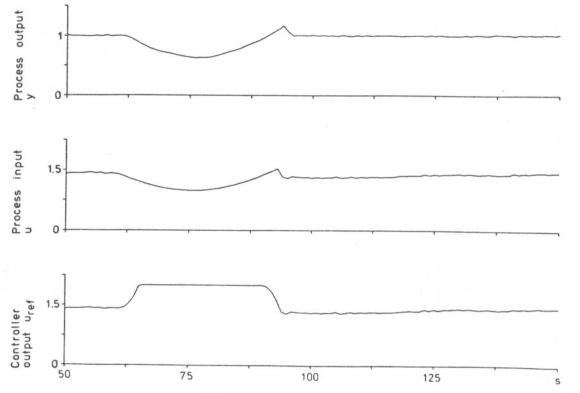

Fig 12 Reset windup, constant integrating controller.

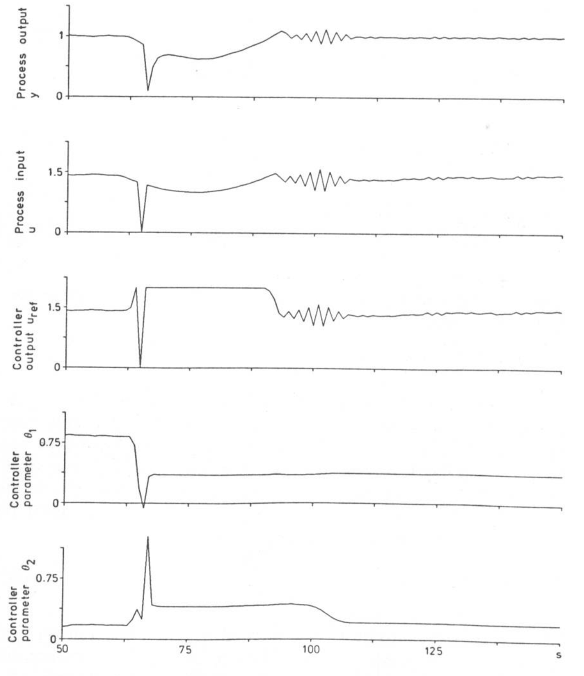

Fig 13 Reset windup, adaptive integrating controller.

if HIGH then HI=u_m, ADAPT=0;
if LOW then LO=u_m, ADAPT=0;

The result can be seen in Fig 15. As long as the limit u_{max} decreases, there are no problems, but when it starts to increase, the behaviour is violent. □

Example 7: The method in Example 6 is changed in the following way. The estimation is not switched on until the second unsaturated sampling instant. Else the method is unaltered. The result can be seen in Fig 16. When the limit u_{max} increases, the control output u_{ref} oscillates, but the data is not used in the estimation. Thus the parameter windup is avoided. The reset windup is handled by limiting u_{ref} to the measured control signal u_m. □

Comparing the three examples, the control output u_{ref} in Example 5 is constant and at the same level as when the saturation started. Only the logical information HIGH or LOW is used. Here the saturation lasts until the available control signal is larger than the value at which the saturation started.