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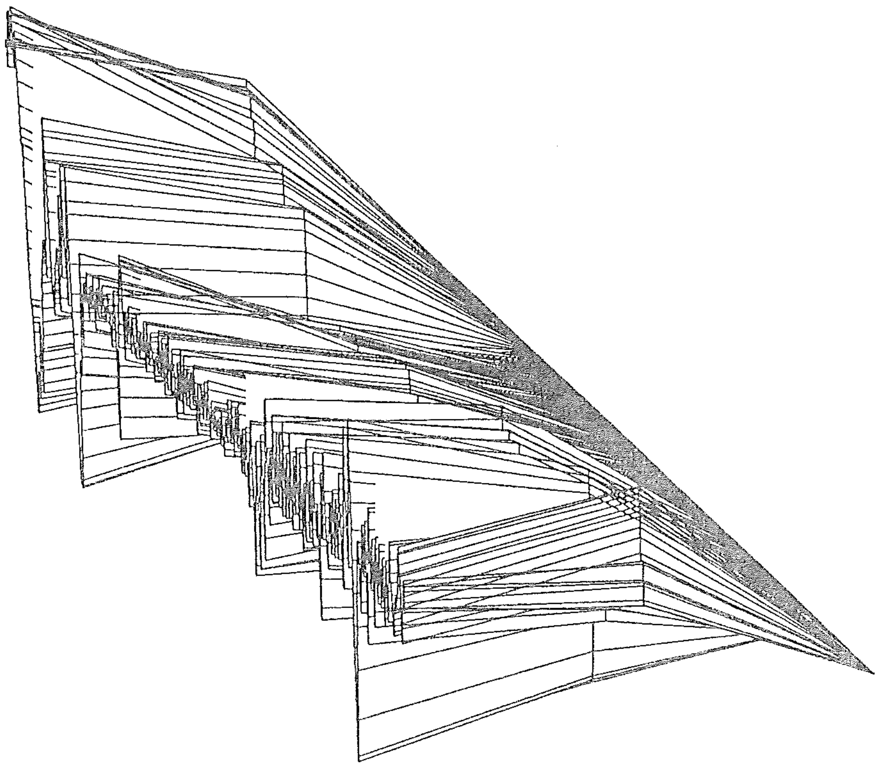
Ulf Holmberg



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Title and subtitle
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Abstract

This thesis is devoted to a special dual control problem arising in the biological part of a waste water treatment plant, the activated sludge system. The main problem is to estimate parameters of a physical model of the dissolved oxygen (DO) concentration dynamics. The parameters, the respiration rate (R) and the oxygen transfer rate (K_La), have a particular interest. The problem becomes difficult because the two parameters are not identifiable with straightforward estimation techniques. At the same time the DO concentration needs to be controlled.

The thesis is split into three separate parts. First there are two published papers presenting the ideas and methods. Experimental results from a full scale plant in Malmö are given in the third part.

Key words
Dissolved oxygen control; oxygen transfer rate; oxygen uptake rate;
respiration rate; estimation; dual control; adapive control; activated sludge;
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Introduction

This thesis is devoted to a special dual control problem arising in the biological part of a waste water treatment plant, the activated sludge system. The main problem is to estimate parameters of a physical model of the dissolved oxygen (DO) concentration dynamics. The parameters, the respiration rate (R) and the oxygen transfer rate (K_La), have a particular interest. The problem becomes difficult because the two parameters are not identifiable with straightforward estimation techniques. At the same time the DO concentration needs to be controlled.

The control problem has been solved earlier by adaptive control schemes, see [4]. However, these adaptive controllers are based upon linear, mathematical models rather than nonlinear, physical ones. Consequently they suffer from the fact that the parameters have no physical interpretation.

The thesis is split into three separate parts. First there are two papers [1-2] presenting the ideas and methods. Experimental results from a full scale plant in Malmö are given in the third part.

In the first paper the estimation problem under open loop is considered. The estimator model is written in a special form to take advantage of the fact that the physical model is linear in its parameters. To achieve this the derivative of the DO concentration must be estimated. A Kalman filter is used as an estimator in both simulations and on real plant data. It is shown that the parameters can be tracked simultaneously in presense of noise. However, the drawbacks are both that the relative changing rate of the parameters must be known and that there is slow convergence. Therefore another idea is presented: Both parameters are updated only in periods when the excitation is high. Between these occasions the assumed slower parameter is frozen and the other parameter (R) is calculated from the DO mass balance equation.

In the second paper the "high excitation idea" is generalized such that no à priori information about the parameters changing rate or relative changing rate is needed. The approximation of the DO derivative is improved by using estimated derivatives of the parameters. Also a dual control strategy is presented. The control idea is the following:

- The model is nonlinear and time-varying. Use a nonlinear and time-varying controller to make the closed loop system linear and time-invariant.
- This requires fast accurate tracking of the parameters. Close the loop with a relay to force the system into a limit cycle. This will give excitation needed for the estimation.

The second paper contains just simulations and no experiments on a real plant. The third part is filling this lack. The ideas from the second paper have been implemented in a real-time language, `Modula2`, on a personal computer. The ideas have then been tested at Sjölundaverket, the major waste water treatment plant in Malmö. The experiments will be discussed in detail in the last section.

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SIMULTANEOUS ON-LINE ESTIMATION OF OXYGEN TRANSFER RATE AND RESPIRATION RATE

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Abstract. Methods for simultaneous estimation of oxygen uptake rate and respiration have been developed. Estimation requires only dissolved oxygen concentration and air flow rate measurements combined with model knowledge. Both parameters are assumed time-varying. The methods are demonstrated in simulations and tested on real data from activated sludge systems.

Keywords. Activated sludge; dissolved oxygen; fermentation; estimation; oxygen transfer; respiration; oxygen uptake rate.

1. INTRODUCTION

The oxygen uptake rate or respiration rate (R) is an essential variable in both fermentation and activated sludge systems. This paper presents an estimation method to find R directly from measurements of dissolved oxygen concentration and air flow rate in an open aerator system. This idea was proposed by Brouzes (1968), among others. The difficulty in calculating R directly from the DO concentration is that the oxygen transfer rate k_La also has to be known. To estimate k_La is not trivial, since it is varies slowly along with R (see Olsson (1984)). Therefore k_La and R have to be estimated simultaneously.

Estimation of k_La and R has been tried elsewhere. Since information about the oxygen transfer rate is useful in several applications it has been estimated separately, while R has been assumed to be constant but unknown, (see Olsson-Hansson (1976), Holmberg (1981)). The value of k_La may indicate both changes in e.g. the water quality and clogging of the air diffusers. Even a membrane failure in the DO sensor may be detected in this way. In an adaptive control simulation study (Ko et al (1982)) R has been assumed constant, which is unrealistic. The servo problem, varying DO setpoint, has been considered instead of the real regulator problem, varying load. In another approach only deviations of R from an (unknown) steady state value could be estimated (see Cook et al (1981)).

The main contribution of this paper is to show that the values of the two quantities can be estimated on-line simultaneously without any steady-state off-set even if both quantities are time varying.

The R and the k_La cannot be estimated simultaneously unless a good use of the system structure is made. Here the nonlinear structure has been retained. Still the model only includes the DO mass balance. Two approaches are presented in the paper. The first is a Kalman filter approach, where the two parameters are tracked simultaneously. It is demonstrated that unbiased estimates are obtained. The second approach uses large singular changes in the air flow signal to rapidly update the oxygen transfer rate, a so-called deadbeat estimator. The two methods can be combined.

The estimator design begins with an appropriate process model, described in the following section. Then the estimator structure is developed first to the Kalman approach and then to the deadbeat estimator. Both simulations and open loop plant experiments are used to evaluate the two methods.

2. PROCESS MODEL

The oxygen mass balance equation for the system under consideration is:

$$\frac{dy}{dt} = -\beta \cdot y + \alpha \cdot u \cdot [c - y] - R \qquad (2.1)$$

where

$y(t)$	dissolved oxygen concentration [mg/l]
$u(t)$	air flow rate [m^3/min]
$R(t)$	respiration rate [mg/(l·h)]
$\alpha(t)$, $\beta(t)$, $c(t)$	time variant coefficients
$\alpha \cdot u = K_La$	oxygen transfer rate [1/h]

Our goal is to identify the parameters α and R. The coefficient α is an unknown function of aerator type, water depth, basin shape and even air flow rate. Aerator clogging accounts for much of the variation in α. Therefore we will instead let α be time dependent and estimate it on-line. The respiration R is the total oxygen utilization rate of the microorganisms in both the primary respiration, used in synthesis, and the endogenous respiration, during decay. Respiration can vary unpredictably due to different loads on the plant and also will be estimated on-line.

In practice β and c are known. The parameter β corresponds to a flow term in the mass balance and flows can be measured rather easily. The saturation concentration c is a function of oxygen partial pressure, temperature, salinity and surfactant concentration. All of these quantities are assumed to be known and are almost constant. It ought to be sufficient to update c now and then without risking accuracy.

3. ESTIMATOR STRUCTURE

Descriptions of time-varying dynamics can be achieved with different mixes of formality and intuition. The respiration R will change significantly in a number of hours while α differs just slightly from day to day, so that in terms of parameter variation α and R have their own estimation requirements.

Earlier attempts have been made to base the estimator on the linearized form of (2.1). This approach has several disadvantages. Since the system seldom is at steady-state there is no obvious point to linearize about. Moreover, the parameters of the sampled system will be complex functions of the parameters of the continuous system (α and R). This will make it difficult for the estimator to take advantage of the knowledge of different time scales of α and R.

Instead of linearizing the right-hand side of (2.1), which yields an unwieldy estimator structure, we prefer to estimate the derivative term, allowing use of the continuous time system directly as the estimator model set. Then the estimator will have a parameter vector $\theta=(\alpha\ R)^T$, consisting of the parameters we are interested in.

An appropriate estimator structure may look like:

$$\hat{\varsigma}(t) = \hat{\theta}^T(t)\varphi(t)$$

where

$$\hat{\theta}(t) = \begin{bmatrix} \hat{\alpha}(t-1) \\ \hat{R}(t-1) \end{bmatrix} \quad \varphi(t) = \begin{bmatrix} u(t-1)[c(t-1)-y(t-1)] \\ -1 \end{bmatrix}$$

$$\hat{\varsigma}(t) = \left[\frac{dy(t-1)}{dt}\right]_{est} + \beta(t-1)\cdot y(t-1)$$

where the first term on the right-hand side is the approximated derivative.

An Euler Approximation of the Derivative

A difference approximation of the kind

$$\frac{dy(t)}{dt} \approx \frac{y(t+1)-y(t)}{h} \tag{3.1}$$

will work well when the sampling interval h is short enough. But in measuring there is always noise which makes it undesirable to use a too short sampling period. A simple way to make the estimator less noise sensitive is to lengthen the sampling interval. The difference approximation will then become poorer as an estimation of the derivative, causing a bias in the parameter estimates.

A Modified Approximation of the Derivative

Assume for the moment that u(t), $\alpha(t)$, $\beta(t)$, c(t) and R(t) are constant during the sampling interval. Then the corresponding sampled mass balance equation from the computer's point of view is:

$$y(kh+h) = y(kh)$$

$$+ h^*\{-\beta(kh)y(kh) + \alpha(kh)u(kh)[c(kh)-y(kh)] - R(kh)\}$$

where $h^* \equiv \dfrac{1-e^{-\gamma(kh)\cdot h}}{\gamma(kh)} = h - \gamma(kh)\dfrac{h^2}{2} + \cdots$

$$\gamma(kh) = \beta(kh) + \alpha(kh)\cdot u(kh)$$

Then by identification of parts we can easily solve for a modified expression for the derivative:

$$\frac{dy(kh)}{dt} = \frac{y(kh+h)-y(kh)}{h^*} \tag{3.2}$$

The above expression for the derivative is exact at the sampling instants if the parameters are constant during the sampling period, which can reasonably be assumed for all the parameters except for R. We can cover this assumption in the case of R by selecting an appropriate sampling interval.

An important difference between the two approximations is that the accuracy of (3.1) is dependent on the total process dynamics, while (3.2) is crucially dependent on just a part of it, R(t). This means that when the derivative is of most importance, during an excitation with u(t), (3.1) will be inaccurate while (3.2) remains accurate so long as R(t) is relatively constant.

4. SIMULTANEOUS TRACKING

A straight-forward recursive least squares approach with a forgetting factor would not be able to take into account the different rates of change of the parameters. Of course that problem is easy to overcome by introducing one suitable forgetting factor for each parameter. However, a severe problem occurs when there is poor excitation; the covariance matrix P in the recursive algorithm may explode.

A better formal treatment is the Bayesian approach, see Ljung and Söderström (1983). Here the parameter vector θ is considered to be a random variable. This approach will not lead to any P matrix explosion risks. The description of the system is a linear regression model with stochastically varying dynamics.

Assume that the true value of the parameter vector θ varies according to

$$\theta(t+1) = \theta(t) + w(t)$$

where $\{w(t)\}$ is a sequence of independent Gaussian random vectors such that w(t) has zero mean and covariance matrix R1(t). This allows us to separate the time scales of α and R by making an educated guess as to their respective variances. The overall description of the system becomes:

$$\theta(t+1) = \theta(t) + w(t)$$
$$\varsigma(t) = \varphi^T(t)\theta(t) + e(t)$$

where

$$\theta(t) = \begin{bmatrix}\alpha(t-1)\\ R(t-1)\end{bmatrix}; \quad \varphi(t) = \begin{bmatrix}u(t-1)[c(t-1)-y(t-1)]\\ -1\end{bmatrix}$$

$$\varsigma(t) \equiv \frac{dy(t-1)}{dt} + \beta(t-1)\cdot y(t-1)$$

and $Ew(t)w^T(s) = R1(t)\delta_{ts}$; $Ee(t)e(s) = R2\delta_{ts}$;
$Ew(t)e(s) = 0$; $Ew(t) = Ee(t) = 0$

Applying the Kalman filter gives the estimates

$$\hat{\theta}(t) = \hat{\theta}(t-1) + L(t)\varepsilon(t)$$
$$\varepsilon(t) = \varsigma(t) - \varphi^T(t)\theta(t-1)$$
$$L(t) = \frac{P(t-1)\varphi(t)}{R2(t) + \varphi^T(t)P(t-1)\varphi(t)}$$
$$P(t) = P(t-1) + R1(t) - \frac{P(t-1)\varphi(t)}{R2(t) + \varphi^T(t)P(t-1)\varphi(t)}$$

Even though the Kalman filter can be shown to converge to the true parameter values, as will be demonstrated in Section 7, it may take a long time if there is no a priori knowledge of the estimates. A way to quicken the estimation is to take advantage of large input excitations to rapidly update the estimates. An approach where singular excitations are utilized is described below.

5. MAKING USE OF SINGULAR EXCITATIONS

Now consider a situation where the air flow rate is changed stepwise. Reconsider the system (2.1) which can be rewritten as:

$$\xi(t) = \alpha(t-1)\cdot\varphi(t)$$

$$\text{where} \quad \xi(t) \equiv \frac{dy(t-1)}{dt} + \beta(t-1)\cdot y(t-1) + R(t-1)$$

$$\varphi(t) \equiv u(t-1)\cdot[c(t-1) - y(t-1)]$$

Let the estimator structure be:

$$\hat{\xi}(t) = \hat{\alpha}(t-1)\varphi(t)$$

$$\text{where} \quad \hat{\xi}(t) = \frac{y(t)-y(t-1)}{h^*} + \beta(t-1)\cdot\hat{y}(t-1) + R(t-1)$$

For this estimator a new equation error ε can be defined.

$$\varepsilon(t) = \hat{\xi}(t) - \hat{\alpha}(t-1)\varphi(t)$$

The "Deadbeat" Estimator Idea

Consider the equation error ε at two different times t_1 and t_2. If ε is negligible and the derivative is estimated without error, the following two equations are satisfied:

$$\varepsilon(t_1) = 0 \Rightarrow \alpha_1 u_1[c-y_1] - R_1 = \hat{\alpha}_1 u_1[c-y_1] - \hat{R}_1$$

$$\varepsilon(t_2) = 0 \Rightarrow \alpha_2 u_2[c-y_2] - R_2 = \hat{\alpha}_2 u_2[c-y_2] - \hat{R}_2$$

To ensure the requirement that $\varepsilon = 0$, the estimate of R is updated with a large gain. This results in a linear system consisting of two equations with four unknown variables, $\alpha_1=\alpha(t_1)$, $R_1=R(t_1)$, $\alpha_2=\alpha(t_2)$ and $R_2=R(t_2)$. To be able to solve this system the number of unknowns has to be reduced. Continuity reasons give:

$$t_1 \to t_2 \Rightarrow \begin{cases} \alpha_1 \to \alpha_2 \\ R_1 \to R_2 \end{cases}$$

Thus if Δt (= $t_2 - t_1$) is chosen small enough to ensure that even the fastest parameter R varies negligibly during the time interval there are only two unknowns. Note that this linear system consists of two different equations only if the input u is significantly different at the time instants considered. Since the time interval must be small such an input change is a sudden singular excitation. If Δt is chosen to be the sampling period, α and R are updated in one step. Thus the name deadbeat.

In practice, during periods of low excitation when noise is a large part of the variation, the Kalman filter is more appropriate than the deadbeat strategy. The algorithm can be divided naturally into two sections. The first is the Kalman filter and the second is built on the special deadbeat corrector. The criterion for switching to the deadbeat corrector depends on the input signals, parameter bias and noise level, etc.. This is the subject of present research.

6. SIMULATION EXAMPLES

This section will demonstrate deadbeat and Kalman parameter estimation using simulation plots. The inputs to the estimator, u and y, are shown in Figs. 6.1 a and b respectively. For simplicity the singular excitation is made by abrupt square wave changes of the air flow rate u. Consider an excitation to be singular (large enough) if $\Delta u > 5$.

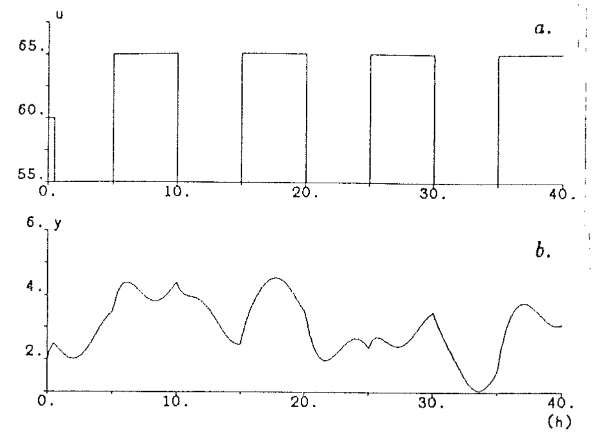

Fig. 6.1 Air flow rate (a) [m^3/min] and dissolved oxygen concentration (b) [mg/l] as input and output to the simulated model.

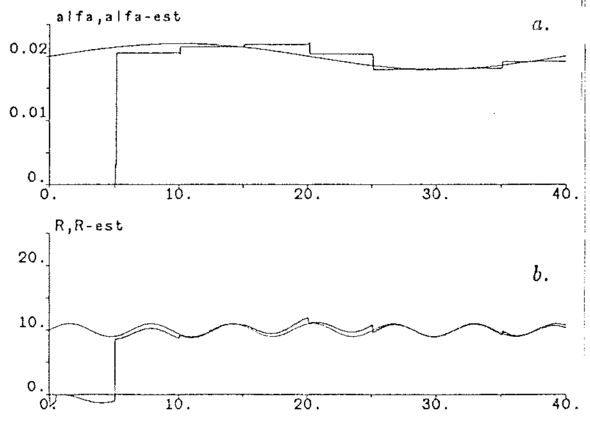

Fig. 6.2 The real and estimated α and $\hat{\alpha}$ (a) and respiration rate R and $\hat{R}$. Notice that $\hat{\alpha}$ is estimated only at a time of singular excitation. Variation of α between excitations gives also a bias in the estimated respiration $\hat{R}$.

Figures 6.2 a and b illustrate the discrete nature of the deadbeat approach. The true parameters are generated as sine-waves:

$$\begin{cases} \alpha(t) = 0.02\cdot[1 + 0.1\cdot\sin(2\pi \frac{t}{T_\alpha})] \quad , \; T_\alpha = 40 \\ R(t) = 10\cdot[1 + 0.1\cdot\sin(t)] \end{cases}$$

The inaccurate in the deadbeat estimates is due to the rapid variation of R during the excitation. The estimates give, however, a good picture of the parameter dynamics. The deadbeat estimator is designed to be used only during singular excitation periods since it is otherwise sensitive to plant and measurements noise. Therefore it has to be combined with a Kalman filter, and can give a quick start-up of the estimates. Also the deadbeat estimator can be executed intermittantly at input excitations to check the parameter tracking.

Figures 6.3 a and b illustrate the tracking capability of the Kalman filter when noise is present. Here, the output y has an additive component of white noise with the standard deviation 0.01. The period of α is T_α = 80, i.e. a change of 10 % in 20 hours.

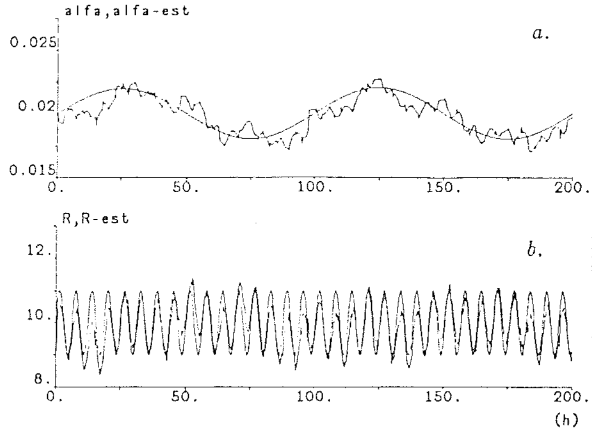

Fig. 6.3 The simulated values and Kalman estimations of α and $\hat{\alpha}$ (a) and respiration rate R and $\hat{R}$ (b) respectively. Despite signal noise and large variation in the parameters, the estimates follow the true values quite well. The dynamic model input is a square wave.

7. ESTIMATION ON PLANT DATA

Two sequences of sampled data of different length and characteristics will now be used. Both sequences come from Käppala Sewage Works, Lidingö, Sweden.

The first one has a length of 5 hours and a special excitation by the air flow rate, (see Fig. 7.1 a). The output (Fig. 7.1 b) responds as a first order system and thus we expect the parameters α and R to vary quite slowly. The main influences on the dissolved oxygen dynamics (y) come from the air flow rate (u). Different choices of initial values for the estimates were chosen to illustrate that the algorithm converges, (see Figs. 7.1 c and d). However, the deadbeat estimator would be helpful to make the convergence faster.

The second data sequence on the other hand, as shown in Figs. 7.2 a and b, is 50 hours. The excitation by the air flow rate (u) is poor with steps at only a few occasions. However, the possibility to estimate α is dependent on the excitation from φ = u(c - y), which is fortunately affected by rapid changes in y. Thus we get relevant information for the α estimation when there is large variation in R even though u is constant. The figures show that the output y changes significantly even though u is constant, indicating that the main influences on the dissolved oxygen concentration (y) here is due to variations in the parameters R and α. The initial value of the estimates are not crucial as illustrated in Figs. 7.2 c and d.

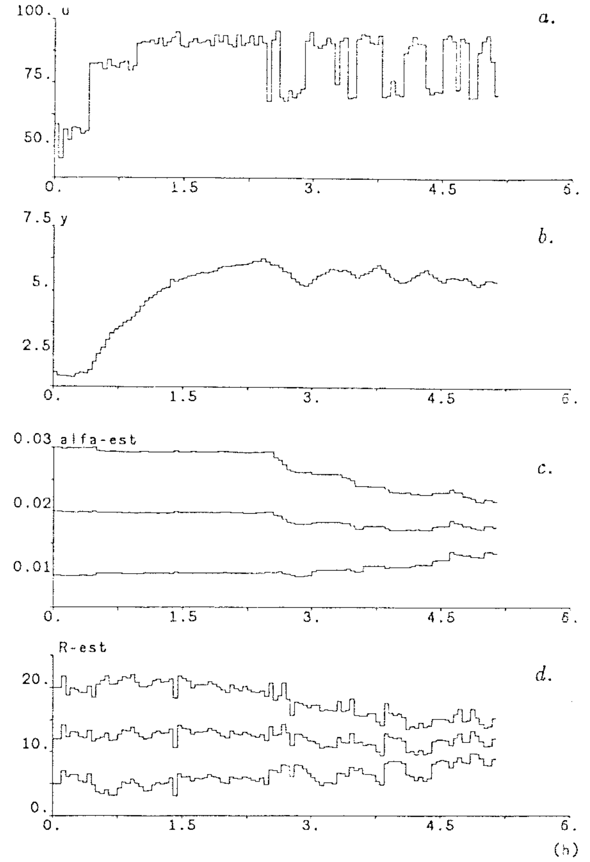

Fig. 7.1 Air flow rate (a) [m^3/min] and dissolved oxygen concentration (b) [mg/l] from the Käppala Sewage Works, Lidingö, Sweden. The sampling interval is 3 minutes. Estimated $\hat{\alpha}$ (c) and $\hat{R}$ (d) started with different initialization of the Kalman filter to show convergence.

8. ESTIMATION AND CONTROL. CONCLUSIONS.

The knowledge of K_La and R may be an end in itself. It has already been mentioned that K_La reflects the efficiency of the aeration system. Knowing R, the specific growth rate or the variations of substrate concentration can be calculated. Also, the knowledge of R is essential for good sludge inventory control in wastewater treatment, see Olsson (1984). The specific oxygen utilization rate in the aerator can be used to specify the target for return sludge control or step feed control in activated sludge systems.

The estimator can be part of an adaptive controller for dissolved oxygen. However, the need for extra air flow excitation should be noted. The use of self-tuning control for the DO has been demonstrated in a full scale application, see Olsson et al (1985). In this application, however, R and k_La were not estimated explicitly. Research is being conducted to learn more about the combination of this estimator with controllers.

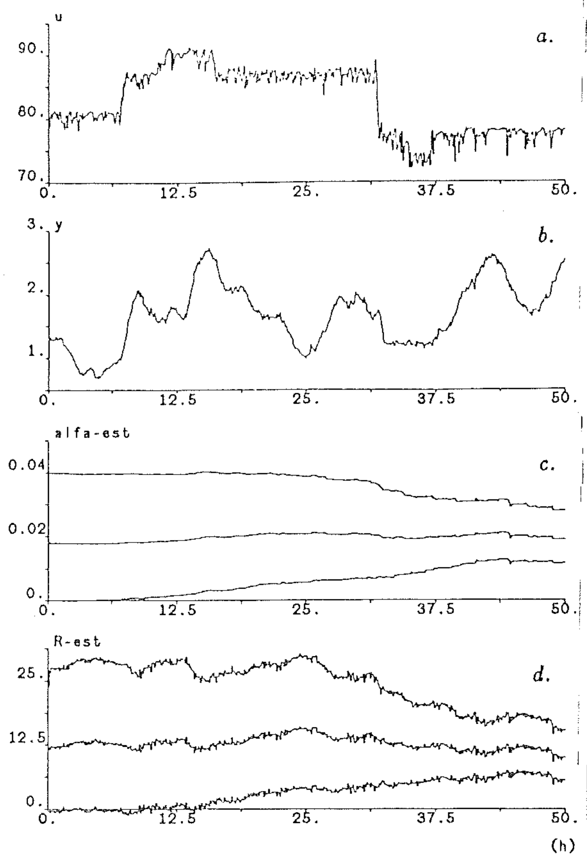

Fig. 7.2 Air flow rate (a) and dissolved oxygen concentration (b) from Käppala. The air flow rate excitations are less frequently than in Fig. 7.1. Crude initial guesses of the estimates $\hat{\alpha}$ (c) and $\hat{R}$ (d) give acceptable convergence. The sampling period is 6 minutes.

Acknowledgements

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REFERENCES

Brouzes, P. (1968). Automated Activated Sludge Plants with Respiratory Metabolism Control. Fourth Int. Conf. on Water Pollution Control Res., Prague.

Cook, S., and S. Marsili-Libelli (1981) Estimation and Control Problems in Activated Sludge Processes. Paper, IAWPRC Workshop on Practical Experiences of Control and Automation in Wastewater Treatment and Water Resources Management, June 20-26, Munich.

Holmberg, A. (1981). Microprocessor-based Estimation of Oxygen Utilization in the Activated Sludge Wastewater Treatment Process. Int. J. Systems Sci., 12, 6, 703-718.

Ko, K.Y., B. C. McInnis and G. C. Goodwin (1982). Adaptive Control and Identification of the Dissolved Oxygen Process. Automatica, 18, 727-730.

Ljung, L., and T. Söderström (1983). Theory and Practice of Recursive Identification. The MIT Press Series in Signal Processing, Optimization and Control, 4, chap. 2.6, pp 54-56.

Olsson, G., and O. Hansson (1976). Stochastic Modeling and Computer Control of a Full Scale Wastewater Treatment Plant. Proc. Symp of Systems and Models in Air and Water Pollution, The Inst. of Measurement and Control, London, Sep.

Olsson, G. (1984). Control Strategies for the Activated Sludge Process. Comprehensive Biotechnology, 3, ch. 30.

Olsson, G., L. Rundqwist, L. Eriksson, and L. Hall (1985). Self Tuning Control of the Dissolved Oxygen Concentration in Activated Sludge Systems. Paper 4th IAWPRC Workshop on Instrumentation and Control of Water and Wastewater Treatment and Transport Systems, Houston, Texas.

ADAPTIVE DISSOLVED OXYGEN CONTROL AND ON-LINE ESTIMATION OF OXYGEN TRANSFER AND RESPIRATION RATES

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Abstract: The paper describes two problems concerning the dissolved oxygen (DO) dynamics in an open aerator of an activated sludge system. The first is an estimation problem where the oxygen transfer rate K_La and the respiration rate R are estimated simultaneously on-line. The second is control of the DO concentration during estimation, using a dual control strategy.

Keywords: Dissolved oxygen control; oxygen transfer rate; respiration rate; oxygen uptake rate; estimation; dual control; adaptive control.

1. INTRODUCTION

Demands on more efficient treatment of wastewater have raised interest in identification of important process parameters, both for better control and for the evaluation of process performance. Control experience with selftuning regulators (STR) have demonstrated the need to compensate for time-varying process parameters. (see Olsson et al (1985)).

The idea of on-line estimation of the respiration rate R in an activated sludge system, given only DO sensor and air flow signals, was proposed by Brouzes (1968), among others. In a covered aerator this problem is straightforward. It is substantially more difficult in the case of an open aerator since R cannot be calculated from the DO mass balance unless the oxygen transfer rate (K_La) is known. Consequently, the problem of simultaneous estimation of K_La and R has been addressed. Different approaches have been suggested. In an adaptive simulation study (Ko et al (1982)) R has been assumed constant, which is unrealistic. Another approach (Cook et al (1981)) did just estimate deviations of R from an (unknown) steady state value. An approach to simultaneous estimation of both the parameters but without control has been presented in Holmberg et al (1985).

Treatment of the continuous nonlinear differential equation describing the oxygen mass balance is begun by putting the equation into discrete form. This presents some difficulties since the system is not only nonlinear but also time variable. Estimators with different complexity and model accuracy will be presented. These estimators include the continuous time parameters as their parameter vector. This is convenient for many reasons. We obtain direct knowledge of the parameters, K_La and R, which have their own interest. Another feature is that the derivative of the parameters can be used in the model structure to maintain a better tracking. No prior assumptions about the parameter variations are made, such as different forgetting factors etc..

It is advantageous to estimate the parameters under closed loop DO control in activated sludge systems. A dual controller using the estimator above will be described and simulated.

The paper is organized as follows: The DO mass balance equation is first described, leading to derivation of the estimator structures. A dual controller is then presented which combines simultaneous estimation and control. Through the paper estimation and control is tested on two contrasting cases of parameter variation, using simulation. Test on real data are planned. Real data experiments without control have been examined in Holmberg et al (1985).

2. PROCESS MODEL

Neglecting flow terms the dissolved oxygen mass balance equation can be described as follows

$$\frac{dy}{dt} = \alpha u(c - y) - R$$

y dissolved oxygen concentration $[\frac{mg}{l}]$

u	air flow rate $[\frac{m^3}{min}]$
R	respiration rate $[\frac{mg}{lh}]$
α, c	time variant coefficients
$\alpha \cdot u = K_L a$	oxygen transfer rate $[\frac{1}{h}]$

Our goal is to estimate the parameters α and R on-line during control of y. The fundamental quantity $K_L a$, the oxygen transfer rate, is here considered to be proportional to the air flow rate u. The coefficient α is a function of aerator type, air production system, water depth, basin shape and even air flow rate and is not known in the practical case. Aerator clogging accounts for much or the variation in α. The respiration R is the total oxygen utilization rate of the microorganisms in both the primary respiration, used in the synthesis, and the endogenous respiration, during decay. Respiration can vary unpredictably due to different loads on the plant. Both of these parameters will be considered to be unknown functions of time and will be estimated on-line.

The DO saturation concentration c is a function of oxygen partial pressure, temperature, salinity and surfactant concentration. All of these quantities are assumed to be known and are almost constant.

3. ESTIMATOR STRUCTURES

The estimator structures we are going to use work in discrete time. Thus the DO equation first has to be put in discrete form, which presents some difficulties since the DO equation is both time-varying and nonlinear. A simple transform is to approximate the derivative using an Euler approximation (difference approximation). This is not appropriate, however, since such an estimator structure gives a bias in the estimates even if the parameters are constant. If the derivative approximation also uses estimated parameters, there will be no bias in the estimates if the parameters are constant. This corresponds to zero order hold sampling. It is therefore convenient to adopt the standard notation for sampled systems (Φ, Γ) when deriving the estimator structure. Since the problem is to track parameters that are not constant, a reasonable generalization is to use estimated derivatives of the parameters. This corresponds to first order hold sampling and will improve the parameter tracking considerably.

Some formal definitions

Reconsider the nonlinear time varying system

$$\dot{y} = \alpha u(c - y) - R$$

Introduce

$$\begin{cases} a \equiv -\alpha u \\ v \equiv \alpha uc - R \end{cases}$$

to transform the nonlinear equation to a linear equation

$$\dot{y} = ay + v$$

Sampling this continuous time linear equation gives

$$y(kh + h) = \Phi y(kh) + \Gamma \tag{1}$$

where

$$\begin{cases} \Phi \equiv \Phi(h) \equiv e^{\int_0^h a(kh+s)ds} \\ \Gamma \equiv \Gamma(h) \equiv \int_0^h \Phi(s)v(kh + h - s)ds \end{cases}$$

It is convenient to define

$$h^* \equiv \int_0^h \Phi(s)ds$$

where the notation will be explained later.

Zero order extrapolation

Assume the parameters a and R and, of course, the input u, to be piecewise constant. Then the state transmission Φ can be expressed in h^* as follows

$$\Phi = 1 + h^* a$$

Note that Φ satisfies

$$1) \quad \Phi(0) = 1$$
$$2) \quad \dot{\Phi} = \dot{h}^* a + h^* \dot{a} = a\Phi \qquad since \quad \dot{a} = 0$$

which are the two conditions for the state transmission. We also have

$$\Gamma = h^* v(kh)$$

Substitution into the sampling equation (1) now gives

$$y(kh + h) = (1 + h^* a)y(kh) + h^* v(kh)$$

$$\Rightarrow \frac{y(kh+h) - y(kh)}{h^*} = ay(kh) + v(kh) = \dot{y}(kh)$$

If the parameter variation is not too rapid during the sampling interval a reasonable approximation of the derivative would be

$$\hat{\dot{y}}(kh) = \frac{y(kh+h) - y(kh)}{h^*}$$

Remark: Compare the similarity with Euler approximation, where instead of the sampling interval h we have substituted for a "generalized sampling interval" h^*.

$$h^* = \int_0^h \Phi(s)ds = \frac{1}{a}(e^{ah} - 1) \approx h + a\frac{h^2}{2} \cdots$$

Having an approximation of the derivative, it makes sense to write the system

$$\dot{y} = \varphi^T \theta$$

where

$$\varphi = \begin{pmatrix} u(c-y) \\ -1 \end{pmatrix} \qquad \theta = \begin{pmatrix} \alpha \\ R \end{pmatrix}$$

and estimate the parameter vector θ from a linear regression model

$$\hat{\dot{y}} = \varphi^T \hat{\theta}$$

Remark: We have to use an old estimate of α in the approximation of the derivative. This means that if we start from scratch the derivative approximation is identical to Euler approximation the first step. Convergence of the estimates will then be helped by the fact that $\hat{\dot{y}}(\hat{\alpha}) \to \dot{y}$ when $\hat{\alpha} \to \alpha$.

But what happens when the parameters are varying? How sensitive is the above described derivative approximation to parameter variation?

The above derivative approximation assumes the parameters are constant during the sampling interval. The error in $\hat{\dot{y}}$ due to parameter variation may then be expressed in $\dot{\theta}$ as described below:

$$S \equiv |\frac{d}{dt}\dot{y}| = |\frac{d\dot{y}}{d\theta}\frac{d\theta}{dt}| = |grad_\theta \dot{y} \cdot \dot{\theta}| = |\varphi^T \dot{\theta}|$$

where S now is a measure of the sensitivity in $\hat{\dot{y}}$ with respect to variations in θ. Note, that not all variation in θ influences the derivative approximation. We are now able to extract two contrasting cases. One where $S \approx 0$, corresponding to the same changing rate in α and R and another where $S \not\approx 0$, corresponding to variations of the parameters in opposite phase.

This is shown in the following figures. The true parameters α and R have been varied with similar changing rates. Fig. 1. illustrates the estimation for the two cases of similar and opposite changes. Note, that no a priori assumption of the variations have been made.

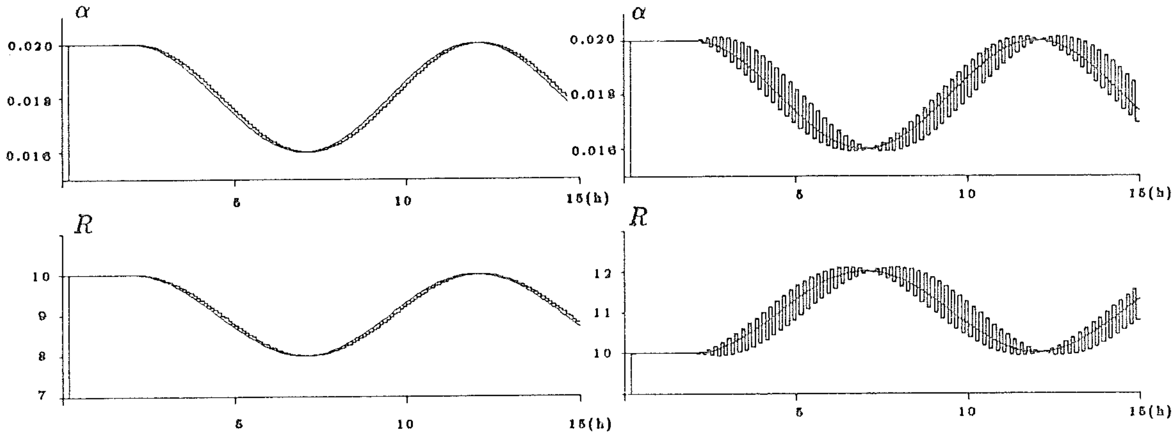

Fig. 1. The parameters α and R when (a) $S \approx 0$ (left) and (b) $S \not\approx 0$ (right).

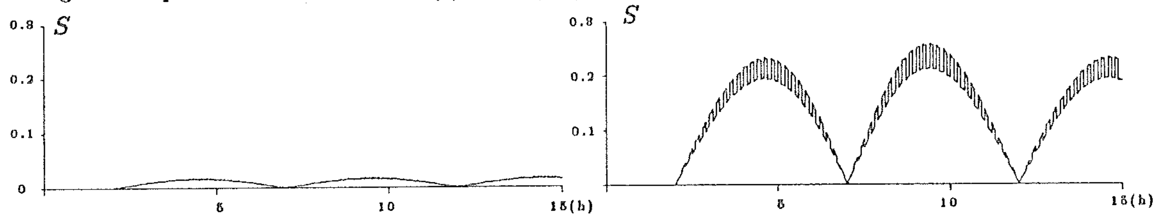

Fig. 1c. The sensitivity S for Figs. 1 a and b.

The estimator used in the above examples will now be described.

The deadbeat estimator

Consider the *DO* equation at two consecutive sampling instants (indexed $()_1$ and $()_2$). Assuming the parameters to be piecewise constant, i.e. $\theta_1 = \theta_2 = \theta$ we can write the the two equations in matrix form

$$\begin{pmatrix} \varphi_1^T \\ \varphi_2^T \end{pmatrix} \theta = \begin{pmatrix} \dot{y}_1 \\ \dot{y}_2 \end{pmatrix}$$

Let the input change at every sampling instant to make the linear equation system well conditioned. Then the following estimator can be used

$$\hat{\theta} = \begin{pmatrix} \varphi_1^T \\ \varphi_2^T \end{pmatrix}^{-1} \begin{pmatrix} \hat{\dot{y}}_1 \\ \hat{\dot{y}}_2 \end{pmatrix}$$

where the estimator is a direct solution of a linear equation algebraic system. Since the estimates converge in finite steps we call this estimator ***the deadbeat estimator.***

First order extrapolation

To handle those cases better when S is significantly larger than zero, a natural step of refinement is to also use information about the parameter derivatives in the approximation of $\dot{y}$.

$$\hat{\dot{y}} = \hat{\dot{y}}(\hat{\theta}, \hat{\dot{\theta}})$$

Assume the parameters to be piecewise linear.

$$\begin{cases} a(kh+t) = a + \dot{a}t \\ v(kh+t) = v + \dot{v}t \end{cases} \quad where \quad \begin{cases} a = a(kh) \quad ; \quad \dot{a} = \dot{a}(kh) \\ v = v(kh) \quad ; \quad \dot{v} = \dot{v}(kh) \end{cases}$$

The state transmission Φ can now be written

$$\Phi = 1 + \int_0^h a(kh+s)\Phi(s)ds = 1 + ah^* + \dot{a}\int_0^h s\Phi(s)ds \tag{2}$$

and

$$\Gamma = \int_0^h \Phi(h-s)v(kh+s)ds = h^* v + \dot{v}\int_0^h s\Phi(h-s)ds$$

Denote the integrals

$$\begin{cases} I_1 = \int_0^h s\Phi(s)ds \\ I_2 = \int_0^h s\Phi(h-s)ds \end{cases}$$

Substitution into equation (1) will now give

$$y(kh+h) = y(kh) + h^*(ay(kh) + v(kh)) + \dot{a}I_1 y(kh) + \dot{v}I_2$$

$$\Rightarrow \frac{y(kh+h) - y(kh) - (\dot{a}I_1 y(kh) + \dot{v}I_2)}{h^*} = ay(kh) + v(kh) = \dot{y}(kh)$$

If the parameter derivatives do not vary too rapidly during the sampling interval a reasonable approximation of $\dot{y}$ would be

$$\hat{\dot{y}}(kh) = \frac{y(kh+h) - y(kh) - (\hat{\dot{a}}I_1 y(kh) + \hat{\dot{v}}I_2)}{h^*}$$

Evaluation of the derivative approximation $\hat{\dot{y}}$.

For the above expression to make sense we have to have some constructive way to calculate the integrals I_1 and I_2. Also, we need to estimate the parameter derivatives. However, the integral expression for h^* does not need to be solved. Instead equation (2) can be used once we have calculated I_1.

$$\hat{h}^* = \frac{1}{\hat{a}_{old}}(\Phi - 1 - \hat{\dot{a}}_{old} I_1)$$

Using the fact that the integrands in I_1 and I_2 are very smooth functions and almost linear when a is small we can try to make a polynomial approximation. If we take one step with a Runge-Kutta of 4^{th} order we get

$$I_1 = \int_0^h s\Phi(s)ds = \frac{h^2}{6}(2\Phi(\frac{h}{2}) + \Phi(h)) + o(h^4)$$

$$I_2 = \int_0^h s\Phi(h-s)ds = \frac{h^2}{6}(2\Phi(\frac{h}{2}) + \Phi(0)) + o(h^4)$$

Estimation of the parameter derivatives

Estimation of the parameter derivatives $\hat{\dot{\alpha}}$ and $\hat{\dot{R}}$ can be done with the least squares method. If n is the number of estimates, the estimated derivative of α is

$$\hat{\dot{\alpha}} = \frac{n\sum_{k=1}^{n}((kh)\hat{\alpha}_k) - \sum_{k=1}^{n}(kh)\sum_{k=1}^{n}\hat{\alpha}_k}{n\sum_{k=1}^{n}(kh)^2 - (\sum_{k=1}^{n}kh)}$$

$\hat{\dot{R}}$ is estimated analogously.

For $n = 3$ and $n = 5$ we get the following estimates for the derivatives:

$$\begin{cases} \hat{\dot{\alpha}} = \dfrac{\hat{\alpha}_3 - \hat{\alpha}_1}{2h} & ; \quad n = 3 \\ \hat{\dot{\alpha}} = \dfrac{2\hat{\alpha}_5 - \hat{\alpha}_4 - \hat{\alpha}_2 - 2\hat{\alpha}_1}{10h} & ; \quad n = 5 \end{cases}$$

Using this information about the parameter derivatives, estimation is greatly improved.

Note that the accuracy of the estimates is greatly improved compared to Fig. 1.

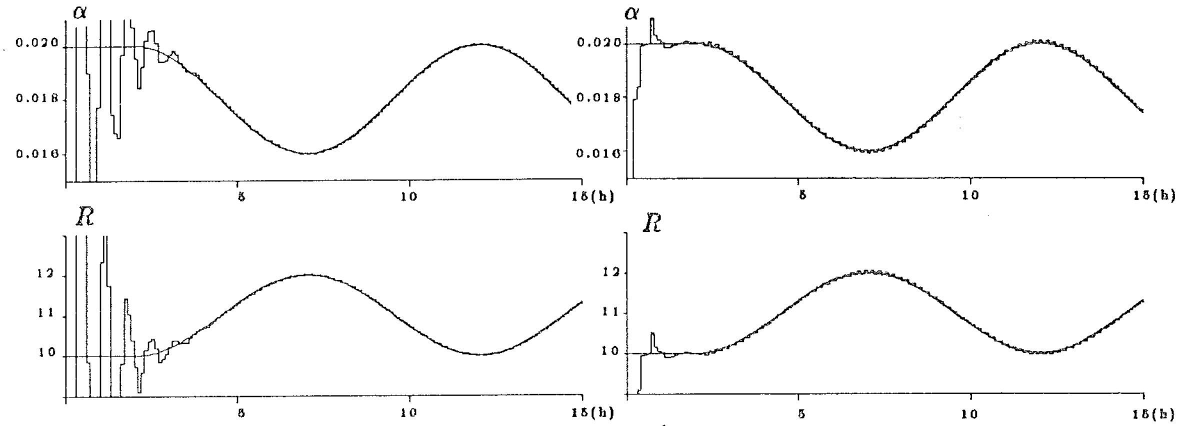

Fig. 2a (left). Real and estimated α and R, when $\hat{y} = \hat{y}(\hat{\theta}, \hat{\dot{\theta}})$ and $n = 3$.

Fig. 2b (right). As Fig. 2a but with $n = 5$.

The deadbeat estimator

Once again consider the DO equation at two consecutive sampling instants one and two steps before the current time. (indexed $()_1$ and $()_2$). Assume the parameters to be piecewise linear, i.e. $\theta = \theta_1 + \dot{\theta}_1 \cdot h = \theta_2 + \dot{\theta}_2 \cdot 2h$. Then the deadbeat estimator, in this case, solves the following linear equation system with respect to $\hat{\theta}$.

$$\begin{pmatrix} \varphi_1^T \\ \varphi_2^T \end{pmatrix} \hat{\theta} = \begin{pmatrix} \hat{\dot{y}}_1 + \varphi_1^T \hat{\dot{\theta}}_1 h \\ \hat{\dot{y}}_2 + \varphi_2^T \hat{\dot{\theta}}_2 2h \end{pmatrix}$$

4. ESTIMATION AND CONTROL

A simple dual controller will now be described. The idea is to use the estimated time-varying parameters in the controller in such a way that the closed loop system tends to become a linear time-invariant system. In order to track the parameters with good accuracy, the deadbeat estimator presented earlier will be used.

The control idea

Once again consider the process

$$\frac{dy}{dt} = \alpha u(c - y) - R$$

Let the setpoint be y_{sp} and the error $e = y_{sp} - y$. Choose the controller

$$u = \frac{\hat{R} + e}{\hat{\alpha}(c - y)}.$$

Then if $\hat{\alpha} = \alpha$ and $\hat{R} = R$ the closed loop system becomes

$$\frac{dy}{dt} = -\frac{de}{dt} = e$$

and we expect the error go to zero exponentially.

Combining Estimation and Control

If the error is kept to zero for a long time with constant input u, we cannot be sure the parameters also are constant. They may drift along the line $\alpha \cdot C = R$, where $C = u(c - y) = \textit{constant}$. Thus, an estimator can give accurate estimates only at occasions when the parameters deviate from this line. During DO control, then, parameter estimation is greatly hindered unless the system is excited in some manner. This leads to the concept of dual control, where a compromise is made between DO-regulation and on-line estimation of α and R.

In the previous Section we used the deadbeat estimator, which involves solving a linear equation system. The linear equation system was made well conditioned by letting the input oscillate every sampling instant. The same idea can be used during control.

The following minor modification of the above control scheme provides the deadbeat estimator with a nonsingular linear equation system even when the error is small. Modifying the control signal with the term $\mathtt{sign}(e)$ we obtain

$$u = \frac{\hat{R} + e + \mathtt{sign}(e)}{\hat{\alpha}(c - y)}$$

yielding for $\hat{\alpha} = \alpha$ and $\hat{R} = R$:

$$\frac{dy}{dt} = -\frac{de}{dt} = e + \mathtt{sign}(e)$$

Parameterization

Introducing parameters in the above control scheme will make it possible to choose in advance the limit cycle amplitude $|\frac{\Delta y}{2}|$. Thus we would like $|\frac{\Delta y}{2}|$ come close to a designated parameter e_{sp} in our regulator.

Looking at the sampling instants, the following controller

$$u = \frac{\hat{R} + a_c e + d \cdot \mathtt{sign}(e)}{\hat{\alpha}(c - y)}$$

gives the closed loop system

$$\frac{dy}{dt} = -\frac{de}{dt} = a_c e + d \cdot \mathtt{sign}(e)$$

when $\hat{\alpha} = \alpha$ and $\hat{R} = R$. The parameter a_c specifies the closed loop pole, i.e. the rate of a step response. Now, we want the parameter d to tune itself during the limit cycle such that $e = \pm e_{sp}$. As an approximate test for limit cycle we can take $|e_t + e_{t-1}| < e_{sp}$. Thus the tuning for d becomes

$$d_{t+1} = d_t + k_d(e_{sp} - |e|)$$

where

$$k_d = \begin{cases} k_d^o & when \quad |e_t + e_{t-1}| < e_{sp} \\ 0 & otherwise \end{cases}$$

Simulations of the two extreme cases studied earlier will now be given during control. The estimator structure using derivatives of the parameters has been used. These derivatives were calculated using 5 estimates as in *Fig.2b*. The controller parameters were $a_c = 10$, $e_{sp} = 0.01$, $k_d^o = 1$ and the initial value $d_0 = 1$.

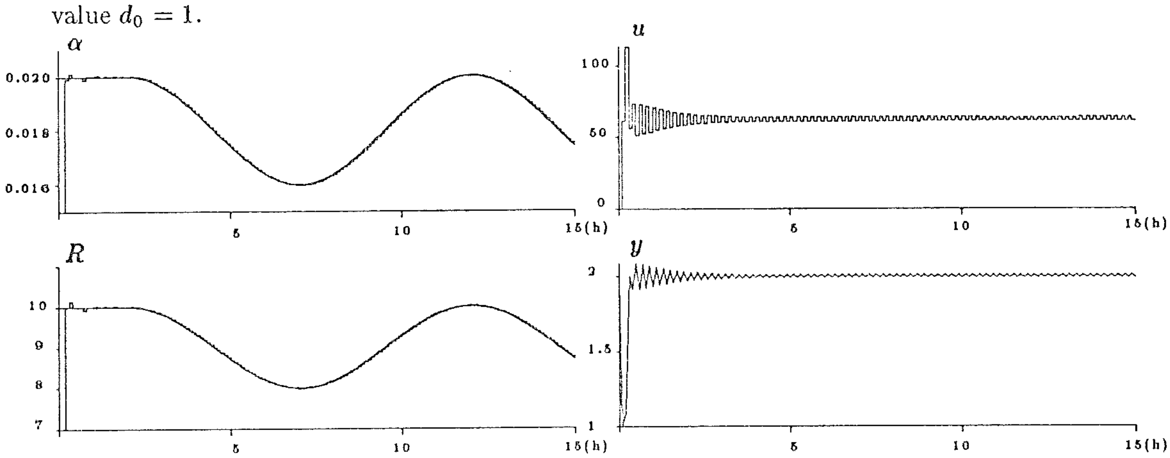

Fig. 3a. The parameters α and R (left). The corresponding input u and output y (right).

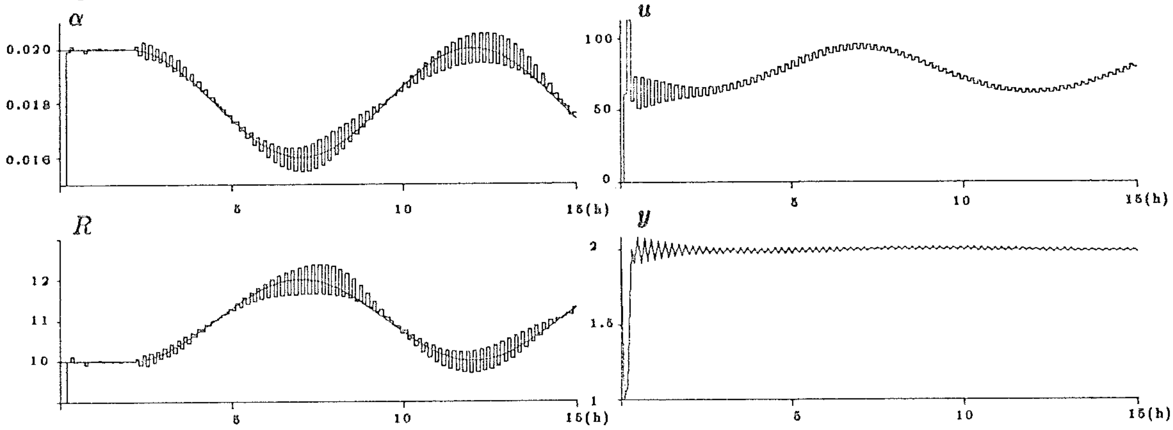

Fig. 3b. As Fig. 3a. but with the sensitivity of $\hat{y}$ to parameter variations $S \neq 0$.

Note the difference between *Fig.2b* and *Fig.3b*. In the latter, a smaller $|\Delta u|$ is used in order to fulfil the constraint $e = \pm e_{sp}$. This influences the quality of the estimated parameters. Clearly, there is a compromise between fast parameter tracking and small error.

It would be desirable to choose a large sampling interval. One reason is that the *DO* model is an approximate description where faster dynamics from the air production system has been neglected. Fast sampling could make the model inaccurate. Another reason is to suppress noise sensitivity. The first order extrapolation method used above will allow a larger sampling period than the zero order method. This is nice since the input u then doesn't need to be changed that often.

5. CONCLUSIONS

Methods for estimating the oxygen transfer rate and respiration rate during control of the dissolved oxygen concentration have been developed.

The estimator structure, working in discrete time, strives to maintain the continuous time structure of the *DO* mass balance equation. This description is made by approximating the derivative. The estimator will then be linear in its parameters, constituting a usual linear regression model.

The control idea is to use the estimated time-varying parameters in the controller in such a way that the closed loop system tends to become a linear time-invariant system. This requires fast accurate parameter tracking. Tracking objectives requires high excitation of the system, contradicting the regulation purpose. Clearly, we have to compromise between regulation and parameter tracking. This compromise is made by introducing a limit cycle in the closed loop system. The oscillations are made sufficiently large to provide the estimator with information about the parameters but small enough so as not to contradict the regulation purpose.

Acknowledgements

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Simnon, developed at the Department of Automatic Control, Lund Institute of Technology. Many thanks to Mr. Craig Elevitch and Dr. Gustaf Olsson for their constructive criticism.

REFERENCES

Brouzes, P. (1968). "Automated Activated Sludge Plants with Respiratory Metabolism Control". 4^{th} *Int. Conf. on Water Pollution Control Res.*,Prague.

Cook, S. and S. Marsili-Libelli (1981). "Estimation and Control Problems in Activated Sludge Processes".*Paper, IAWPRC Workshop on Practical Experiences of Control and Automation in Wastewater Treatment and Water Resources Management*,Munich.

Holmberg, U., Olsson, G. (1985). "Simultaneous on-line estimation of oxygen transfer rate and respiration rate". *Paper,* 1^{st} *IFAC Symposium on Modelling and Control of Biotechnological Processes*, Noordwijkerhout, The Netherlands.

Ko, K.Y., B.C. McInnis and G.C. Goodwin (1982). "Adaptive Control and Identification of the Dissolved Oxygen Process". *Automatica*,18, 727-730.

Olsson, G., L.Rundqwist, L. Eriksson, L. Hall (1985). "Self-tuning control of the dissolved oxygen concentration in activated sludge systems". *Paper,* 4^{th} *IAWPRC workshop on Instrumentation and Control*, Houston, Texas. Published in Drake, R. A. R. (Ed.) *Instrumentation and Control of Water and Wastewater Treatment and Transport Systems*, Pergamon Press, London.

Runge-Kutta methods are described in

Vidyasagar, M. (1978). *Nonlinear Systems Analysis.* Prentice-Hall, Inc. Englewood Cliffs, New Jersey.

Plant Experimentation

Experiments on a full scale plant have been made. In spite of some practical problems, which will be discussed, the dual control algorithm seems to work as expected. The physical parameters R and K_La have been estimated during control of the DO concentration at a specific point along the biological reactor. A description of the relevant part of the plant will be given. Then the operator communication on the personal computer is briefly illustrated by a typical start-up scenario. The practical aspects are discussed together with the given experiments. Then a summary and suggestion for future research end the thesis.

1. Plant Description

The estimation and control ideas have been tested at Sjölundaverket, the major waste water treatment plant in Malmö. The plant is designed to serve 550 000 person equivalents but a normal load is about 400 000. A normal water flow rate is about 1 300 l/s. The total flow is split between an activated sludge system and a fixed film reactor system. The former system is divided into three parallel double basins, each one of them having a volume of 3 300 m^3. The outline of one such double basin is shown in Fig. 1. The hydraulics of the basin is considered as described by four complete mix reactors in series. Since only the total air flow and not the air flow distribution can be manipulated the DO concentration along the basin will display a typical profile. Four DO probes are located in the basin. The controller uses one probe for DO measurements and acts on the total air flow rate. The upstream DO sensor can represent the influent DO concentration to the tank. Thus one fourth of the basin is assumed to behave like a complete mix reactor.

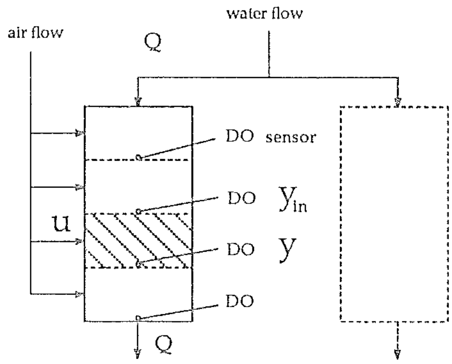


Fig 1. The biological reactor

2. Computer installation

The dual controller is implemented in `Modula2` on a personal computer with real-time facilities. At least four inputs are necessary for the control, i.e. the air flow rate, u, the influent flow, Q, the influent DO concentration, y_{in}, and the controlled DO concentration, y. However, if corresponding signals

(u, Q, y_{in}, y) from other parts of the reactor are measured, not only estimation of parameter variation in time but also in space along the basin is possible. In this case estimation on four different places can be performed to establish a profile. The respiration rate profile is of particular interest. We would like to have the respiration rate equal to the endogenous respiration rate in the end part of the basin, such that the concentration of biodegradable substrate is negligible. Thus, the profile appearance is connected to the choice of *DO* setpoint, see [3].

Just one of the four points can be controlled at a time. In one experiment the 3/4-point along the basin was controlled as indicated by Fig 1. The 1/2-point has also been chosen for control. It is easy to change control point. After the AD-channels have been redefined to correspond to the chosen point the only work that has to be done is recalibration of the air flow rate setpoint. This is necessary since the air distribution along the basin is nonuniform.

A block diagram of the *DO* loop is given in Fig. 2. The upper loop is the existing plant control system. The lower loop is the experimental dual control set-up. Compare with Fig. 1.

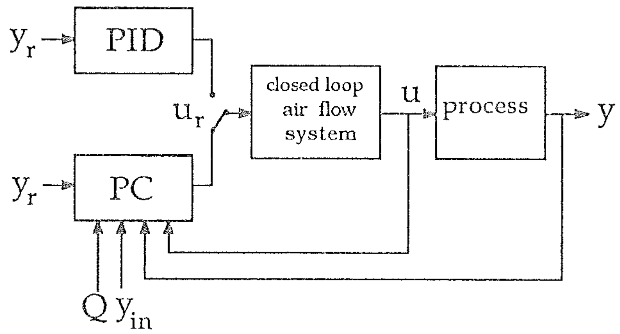


Fig. 2. The *DO* loop. The lower loop is the dual control system

3. The air flow rate control system

In the *DO* model, the air flow rate dynamics is neglected. This is justified by the different time constants for the *DO* loop, $15 - 20$ minutes, and the air flow rate loop, $15 - 20$ seconds. Unfortunately, this separation in time may be destroyed by time delays introduced by the air flow controller. It should be pointed out that this is just practical problems connected with the particular plant air flow control system. But even though this is a plant specific problem the air flow control system will be described briefly since it has caused most of the troubles during the experiments.

The air flow rate control system is shown in Fig. 3. The air flow rate, u, is composed by 2 parts: one part that is varied continuously, $u_c \in [u_{cMin}, u_{cMax}]$, and another part that can take only 3 different values, $u_d \in \{0, u_{low}, u_{high}\}$. The transition condition between the three states of u_d is that u_c is at an end value, u_{cMin} or u_{cMax}, during at least half a minute. Also there is hysteresis added to the transition limits to prevent u_d from toggling between two states. The delay of half a minute is due to the fact that the transition condition is evaluated only twice a minute. Since the evaluation is based on the measured air flow rate, u, and not the set point, u_r, it may very well happen a transition fails just because of some noise or a wrongly calibrated air flow rate sensor. These fatal errors cause severe problems for the dual controller.

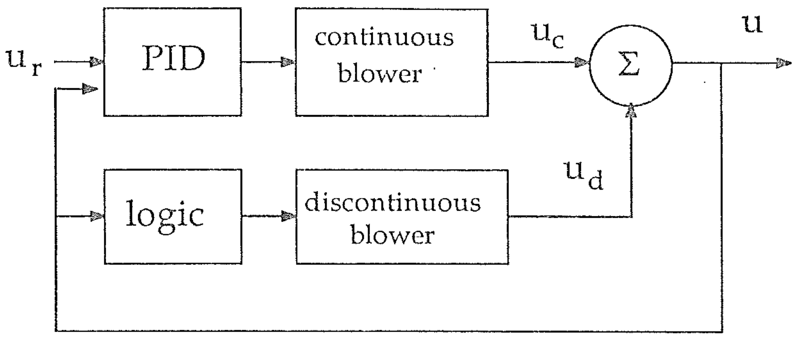


Fig. 3. The air flow rate control system

4. Operator Communication

The operator communication is driven partly from the mouse and partly from the terminal. Basic actions such as start/stop of estimator, regulator, logging and exit the program are driven from the mouse. Stored data and estimates can be shown in graphical plots by actions from the mouse. All parameters are set from the terminal in different dialogue levels. These levels are described in the appendix.

To give some feelings for how the various commands can be used a scenario of a typical start-up will be given.

Start-up Scenario

Commands		Comments
>PLANT		Enter dialogue to set plant specific parameters
P>		The prompt P indicates dialogue mode for PLANT
P>what		Default values for plant parameters are displayed: the volume, V, saturation constant, c, and scale constants urs, us, ys, Qs defining range in engineering unit
P>urs	900	Change scaling constant for the set point u_r
P>what		Display temporary parameters
P>exit		Transfer the parameters to the monitor and exit dialogue
>		The prompt indicates main level command mode
SHOW		Mouse action to show the data u and y in automatic scaling. Let us assume they are varying around 500 m^3/h and 2 mg/l respectively.
>PLOT		Enter dialogue to set scaling of the on-line plot area
P>ubias	500	Subtract a bias from the on-line plotted u
P>ybias	2	Subtract a bias from the on-line plotted y.
P>exit		Transfer the parameters to the monitor
		Now the on-line plotted data u and y will appear in the middle of respective plot area.
>h	2	Set sampling period of plotted and logged data to 2 min.
>nhdual	6	Set sampling period of the dual controller to nhdual $\cdot h = 12$ min

>SIGNAL		Enter dialogue for signal generator
S>mean	500	Set mean of square wave $[m^3/h]$
S>amp	50	Set amplitude of square wave $[m^3/h]$
S>exit		Transfer the parameters to the monitor
>		
Estim On		Mouse action to start estimator
		Wait a couple of samples until the parameters have converged.
SHOW		Show estimated parameters $\hat{\alpha}, \hat{R}$ and u, y in automatic scaling.
Regul On		Start regulator

5. Experiments

"Reality doesn't obey us" —Alexander Dubcek 1968

A selection of experiments will now be presented. Different sampling rates, regulator parameters and control points along the reactor have been investigated. The parameter K_La has been assumed to be proportional to the air flow rate, u, i.e. $K_La = \alpha \cdot u$. Thus the time-varying parameter α is estimated together with the respiration rate R.

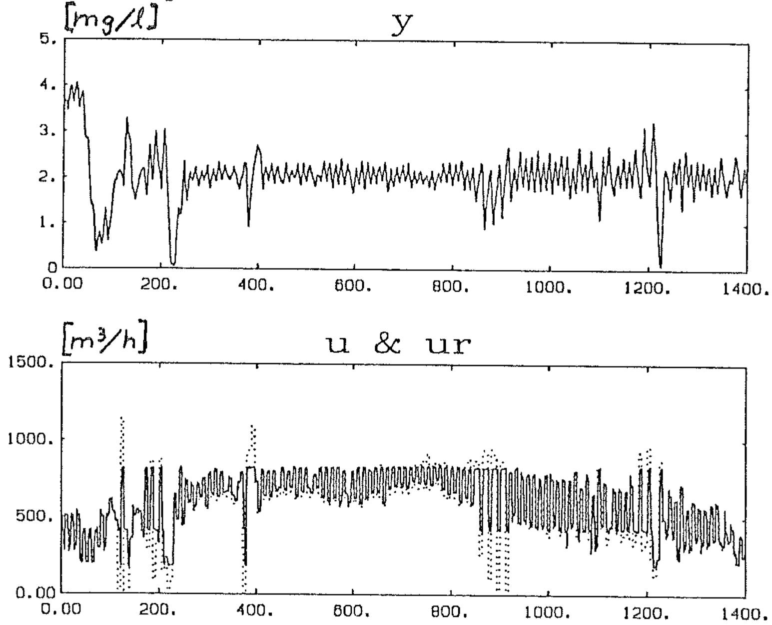


Fig. 4a. The controlled DO conc. y, the air flow rate u (solid) with setpoint u_r (dotted)

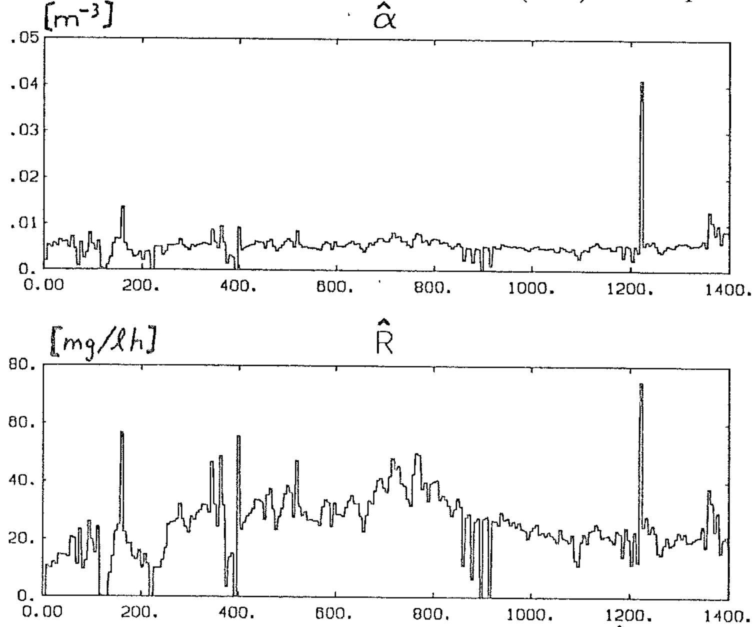


Fig. 4b. The estimated parameters $\hat{\alpha}$ and $\hat{R}$

Experiment 1. (Fig. 4 a-c)

In this experiment the sampling period of the controller was 6 minutes. To be able to see what happens between the sampling instants every minute data has been logged and is plotted in Fig. 4a. This is a 24 hours experiment from a Thursday afternoon to a Friday afternoon. First the signal generator has been used to generate a square wave on different levels for calibration of the air flow rate setpoint u_r. The calibration is already acceptable since u_r (dotted curve) coincide with u (solid curve), measured at the 3/4-point along the reactor. After about 100 $min.$ the control is turned on. The set point, y_{sp}, or the mean of the limit cycle, was chosen to 2 mg/l. The error setpoint, e_{sp}, which is the desired limit cycle amplitude, was chosen to 0.2 mg/l.

On some occasions the estimated parameters have "outliers", see Fig. 4b. These erroneous updatings occur when the input u is not changing between two consecutive sampling instants. Then the excitation needed to get information about the parameters is lacking. What actually happens is that the estimator solves an ill-conditioned equation system (see [2], section 3, dead-beat estimator). Safeguards against such failures have been added to the code after this experiment. The dual controller clearly manages to recover immediately after these failures which illustrates that there is no need for à priori information about the parameters for a start-up.

A plant load maximum usually appears in the middle of the night. That doesn't mean people in Malmö have strange night habits. The load top that is produced by people and industries during the day will reach the waste water treatment plant towards the night.

The respiration rate, R, can be seen as an indicator of the biodegradable substrate load. The estimated respiration rate, $\hat{R}$, has a top in the middle of the night (i.e. between 700 and 800 min), which makes sense. The estimated parameter $\hat{\alpha}$, which is reflecting the efficiency of oxygen transfer from gas to soluble form, is practically constant during the night. That is also expected.

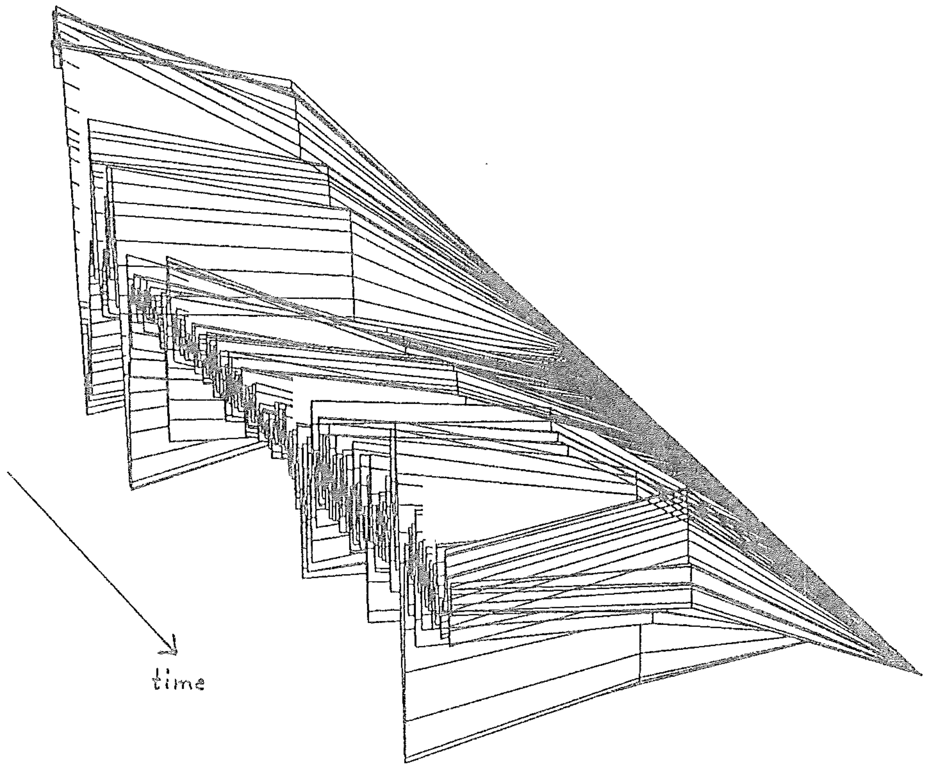


Fig. 4c. Influent DO conc. y_{in} (right) and controlled DO conc. y (left) in a 3-d plot.

The parameters were estimated only at the 3/4-point along the reactor in this experiment. To illustrate that there is a considerable respiration rate profile along the reactor a 3-dimensional plot of the DO concentration is shown in Fig. 4c. The inlet is to the right (the 1/2-point) and the outlet to the left (the 3/4-point). Compare with y in Fig. 4a. It is clearly seen that it is the 3/4-point that has been chosen for control.

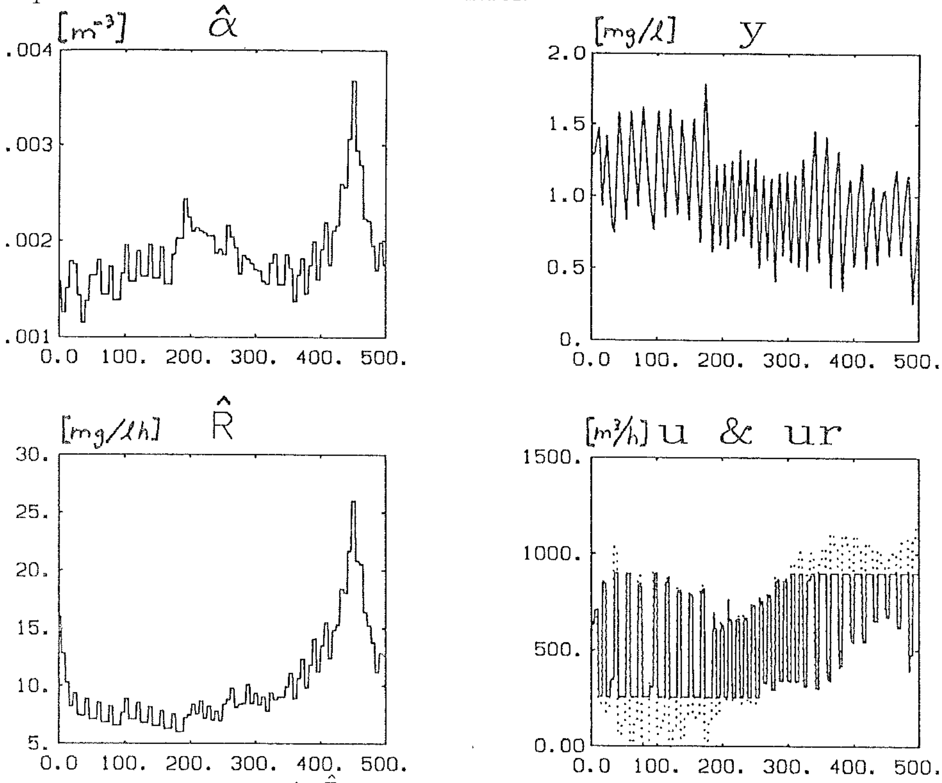


Fig. 5. Estimated parameters $\hat{\alpha}, \hat{R}$ (left). Output y (above), input u with setpoint u_r (below).

Experiment 2. (Fig. 5)

After some problems with the DO sensor at the 3/4-point (probably bubbles on the membrane causing outliers) the control was shifted to the still healthy DO sensor at the 1/2-point. The results are plotted in Fig. 5. This point is much more difficult to control than the 3/4-point. The reason for this is mainly because the parameter α is smaller; about $2 \cdot 10^{-3}$ at the 1/2-point (Fig. 5) compared to about $5 \cdot 10^{-3}$ at the 3/4-point (Fig. 4b). This both makes the dynamics slower and reduces the control authority. The smaller value is probably caused by more clogging of the diffusers near the inlet depending on a higher oxygen demand. Also the estimated respiration rate, $\hat{R}$, is much smaller here than in the 3/4-point. This is, however, **not** expected. Instead one would expect a larger value such that the respiration rate is decaying monotonically along the reactor. The bias in $\hat{R}$ can be explained by a model mismatch of K_La. We have assumed K_La to be proportional to the air flow rate u, i.e. $K_La = \alpha \cdot u$. Independent aerator experiments have indicated that this is the case in the 3/4-point. But what happens if there is a bias term, β, in K_La, i.e. $K_La = \alpha \cdot u + \beta$? The answer is that there will appear a bias in $\hat{R}$. This can be seen from the following calculations.

Reconsider for brevity the model without flow terms.

Process	Model
$\dot{y} = (\alpha u + \beta)(c - y) - R$	$\dot{y} = \alpha u(c - y) - R$

Neglect the error in the approximation of $\dot{y}$ and assume the parameters to be constant. Then the following equality holds:

$$\begin{pmatrix} u_1(c - y_1) & -1 \\ u_2(c - y_2) & -1 \end{pmatrix} \begin{pmatrix} \hat{\alpha} \\ \hat{R} \end{pmatrix} = \begin{pmatrix} u_1(c - y_1) & -1 \\ u_2(c - y_2) & -1 \end{pmatrix} \begin{pmatrix} \alpha \\ R \end{pmatrix} + \beta \begin{pmatrix} (c - y_1) \\ (c - y_2) \end{pmatrix}$$

and the deadbeat estimator (see [2], section 3) will give the result

$$\begin{cases} \hat{\alpha} = \alpha + \beta \dfrac{(y_1 - y_2)}{u_2(c - y_2) - u_1(c - y_1)} \approx \alpha \\ \hat{R} = R + \beta \dfrac{u_1(c - y_1)(c - y_2) - u_2(c - y_2)(c - y_1)}{u_2(c - y_2) - u_1(c - y_1)} \approx R - \beta(c - y_{sp}) \end{cases}$$

when $y_1 \approx y_2 \approx y_{sp}$.

Independent laboratory experiments have shown that R is of the order $20 - 30$, which corresponds to $\beta \approx 1 - 2$. The corresponding value of β in the 3/4-point, however, is much closer to 0.

The setpoint was chosen to $y_{sp} = 1\ mg/l$ and the limit cycle amplitude $e_{sp} = 0.2\ mg/l$. The sampling period was 6 minutes the first 190 minutes. Then it was shifted to 9 minutes. Still there were 6 AD-conversions during every sample which means that the time scale of the plot changes from 1 $min.$ to 1.5 $min.$.

It is reasonable to choose a larger sampling interval in the middle of the basin than in the 3/4-point since the dynamics is slower. Immediately after the change the saturation problem of the air flow rate disappears and the parameter estimates become smother. Also the limit cycle centers around y_{sp} and the amplitude reduces to the prescribed e_{sp}. Then after the 320th sample the air flow rate saturates again. The control starts to deteriorate and the lack of excitation cause the parameter estimates to drift away with each other. Note that they didn't do that before.

6. Summary

Ideas about parameter identification and control have been presented in two separate papers ,[1] and [2]. The first paper, [1], deals only with the identification part. Here, different strategies for on-line estimation of the oxygen transfer rate K_La and the respiration rate R are discussed. One of these ideas is also tested on real plant data. However, that estimator has some disadvantages in terms of convergence rate and need for à priori information. The other estimation scheme discussed hasn't got those drawbacks. But instead it requires excitation by the air flow rate.

The concept to use a special input to the system in order to simplify the estimation is developed further in [2]. It is also shown that such an input can compromise between estimation and control, i.e. a dual control strategy. This dual control scheme has been implemented in `Modula2` on a personal computer. Full scale experiments have then been done.

Experiment experiences

Control and estimation of two different points along the reactor has been done; the 1/2-point and the 3/4-point. It was noticed that it was easier to control the 3/4-point because of more control authority there. However, problems with the DO sensor at that point forced us to continue the experiments in the middle of the basin. During the night when the respiration rate is increasing significantly the controller will saturate. This unables parameter tracking since there is no excitation to the system. The lack of excitation will cause the parameters to drift away together with each other.

The saturation problem is particularly present when controlling the 1/2-point. For a long time the air flow rate control system was the largest problem. Transitions between different states of the blower machine didn't occur when it should. This problem was, however, eliminated when the air flow rate setpoint instead of the measured air flow rate was used in the transition conditions.

Engineering significance

The oxygen transfer rate, K_La, and the respiration rate, R, contain important information about the process. On-line estimate of these quantities will therefore be of great value for a process engineer.

The estimated oxygen transfer rate will for example indicate how far the diffuser clogging has gone and thus be a signal for cleaning of the air production system. It may also be used for DO probe checking and signal for recalibration of a DO sensor.

The respiration rate is a load and toxic indicator. It is therefore interesting both for control and for diagnostics. The estimate has been used here in the DO loop but it may also be fed into other control loops, e.g. step feed control. For example when the estimate, $\hat{R}$, reveals that toxics have entered the system the flow can be bypassed to save the bacteria. The respiration rate profile along the basin has a special interest. It is connected to the choice of DO setpoint, [3].

Suggestions for future research

What is good for estimation is not necessarily good for economy. The input; the air flow rate; is changing quite a lot. Compared to the present plant control system the dual controller changes the air flow more seldom but with larger amplitude. The large changes may be bad for the blower machines. There is a valve distributing the air flow rate between the two parallel basins. This valve has been stationary during these experiments. Perhaps this valve can be used to let the two basins oscillate against each other to provide excitation. This will spare the blower machines and also raise the control authority. However, the load is almost the same to the two basins. Thus good control of one basin by the distributing valve will probably be to the price of worse control of the other basin.

The plant will soon be equipped by an "off-gas" device for the measurement of aeration capacity. The oxygen that is not solved into water is collected and measured, which gives the oxygen transfer rate K_La. Since the DO concentration is also measured the respiration rate can be calculated. Thus the tool can be used to measure the wanted parameters at some point along the reactor. The device does not outdo the dual controller since it is very expensive and can only be used at one point while the estimator can estimate the profile. Estimation of the respiration rate in the middle of the basin gave a bias in the estimate. This was probably caused by a bias term in K_La. The off-gas technique can be used to calibrate the estimator for that bias.

The generalization of the estimator that takes advantage of the estimated parameter derivatives has not been used with success. The estimates need to be smoother to get this to work. Lack of excitation caused by saturation has made this impossible. If such practical issues are solved and more suitable regulator parameter and sampling period are chosen perhaps this also works.

Clearly more experiments need to be done. Also the controller should be tested on other plants to see what is and what is not plant specific problems.

7. Acknowledgements

The research has been partially supported by the National Swedish Board of Technical Development (STU contract 86-3552). A special thank is given to my supervisor Prof. Gustaf Olsson for invaluable discussions. Also the Sjölunda plant personnel are acknowledged, especially Bengt Andersson and Claes Hansson. A lot of people at the department have been of valuable support. Rolf Braun has contributed with hardware equipment for signal conversions. Leif Andersson has streamlined the use of Modula2 on the personal computer. Most of the ideas about the real-time program structure, graphics and operator communication came from Michael Lundh. Per Hagander and Anders Wallenborg have contributed with procedures that write and read data from a file.

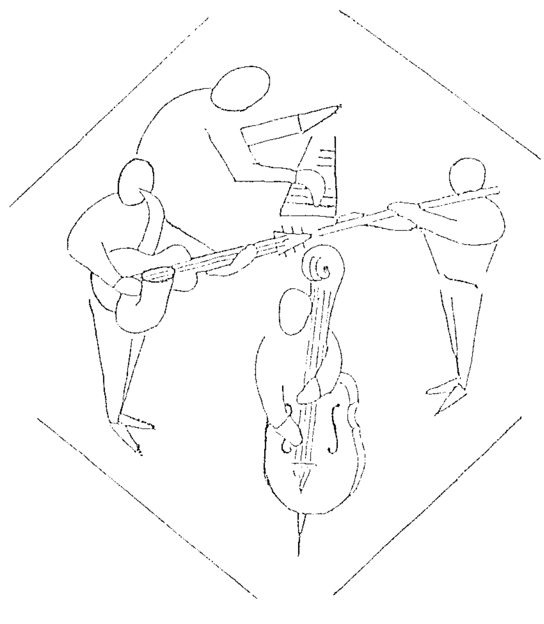
References

[1] HOLMBERG, U. and G. OLSSON (1985): "Simultaneous On-line Estimation of Oxygen Transfer Rate and Respiration Rate," 1^{st} *IFAC Symposium on Modelling and Control of Biotechnological Processes*, Noordwijkerhout, The Netherlands, 11-13 Dec, 1985.

[2] HOLMBERG, U. (1986): "Adaptive Dissolved Oxygen Control and On-line Estimation of Oxygen Transfer and Respiration Rates," *AIChE's Annual Meeting,*, Miami Beach, Nov. 7, 1986.

[3] OLSSON, G. and J. F. ANDREWS (1978): *Water Research*, Vol. 12, pp. 985 to 1004, Pergamon Press Ltd. Printed in Great Britain..

[4] RUNDQWIST, R. (1986): "Self-tuning Control of the Dissolved Oxygen Concentration in an Activated Sludge System," Techn. lic. Thesis CODEN: LUTFD2/TFRT-3180, Department of Automatic Control, Lund Institute of Technology, Lund, Sweden.



The author and his fellow-musicians in *Kvälljazz*

Appendix

Main level commands

Estim On/Off	(mouse)	Start/Stop Estimator
Regul On/Off	(mouse)	Start/Stop Regulator
DISP	(mouse)	Show content in monitor
SHOW	(mouse)	Plot estimates and data in automatic scaling
Log On/Off	(mouse)	Start/Stop logging in file Data.txt
EXIT	(mouse)	Exit the program
SIGNAL	→dialogue	Set parameters for signal generator
ESTIM	→dialogue	Set estimates and estimator structure
REGUL	→dialogue	Set regulator parameter
PLOT	→dialogue	Set scales in the on-line plot area
PLANT	→dialogue	Set plant specific parameters
h	[minutes]	Set AD-converter sampling interval
nhdual	[# of h]	Set sampling interval

Dialogue commands

— Common dialogue commands

WHAT	What do we have? Display current parameters.
QUIT	Exit with no transfer of parameters to monitor
EXIT	Exit with transfer of parameters to monitor

— Dialogue for SIGNAL

MEAN	[real]	Set mean of square wave
AMP	[real]	Set amplitude of square wave

— Dialogue for ESTIM

Alpha	[real]	Set α
R	[real]	Set R
n	[0, 3 or 5]	Set n in $\hat{\theta} = \hat{\theta}(\theta_1, \theta_2, \ldots \theta_n)$

— Dialogue for REGUL

Ac	[real]	Set closed loop pole
esp	[real]	Set setpoint for limit cycle amplitude
d	[real]	Set initial relay gain
kd0	[real]	Set adjusting rate of relay gain

— Dialogue for PLOT

ubias	[real]	Set subtracted bias for u
uscale	[real]	Set scaling for u
ybias	[real]	Set subtracted bias for y
yscale	[real]	Set scaling for y
Maxshow	[1-900]	Set number of old estimates plotted with SHOW

— Dialogue for PLANT

V	[m^3]	Set volume
c	[real]	Set DO concentration saturation constant
urs	[real]	Set scaling for ur
us	[real]	Set scaling for u
ys	[real]	Set scaling for y
Qs	[real]	Set scaling for Q