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PRACTICAL IDENTIFIABILITY OF A BIOKINETIC MODEL OF ACTIVATED SLUDGE RESPIRATION

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Abstract—This paper deals with the estimation of the parameters of the Monod model for the activated sludge process on the basis of oxygen uptake rate data only. The objective of the paper is to concentrate on the practical identifiability properties of the model and on the design of informative experiments for parameter estimation. The results are illustrated by experimental data. Improvements in parameter estimation accuracy with a factor 2 can be obtained by small extensions of the respirometric experiments. The optimal experimental design procedure for parameter estimation (OED/PE) can be implemented in the respirographic sensor.

Key words—activated sludge wastewater treatment, parameter estimation, optimal experimental design, respirometry

NOMENCLATURE

C_ε = measurement error covariance matrix
E = expected value
F = Fisher information matrix
J = objective functional
K_{m1} = saturation or affinity constant (mg/l)
N = number of data
OUR_{ex} = exogenous oxygen uptake rate (mg/l·min)
Q_ε = weighting matrix
S = substrate concentration (mg/l)
t = time (min)
t_{puls} = time of additional substrate pulse injection (min)
V = estimation error covariance matrix
X = biomass concentration (mg/l)
Y_1 = yield coefficient
y = measured output

Greek letters

λ = eigenvalue
μ_{max1} = maximum specific growth rate (min^{-1})
θ = parameter vector
σ = pulse width

Abbreviations

OED/PE = optimal experimental design for parameter estimation.

1. INTRODUCTION

The identification of the dynamical models describing activated sludge processes is characterized by two important features:

1. The models are most often highly complex, they are usually high-order non linear systems incorporating a large number of state variables and parameters. For instance, the IAWQ activated sludge model No. 1 (Henze *et al.*, 1986) contains 13 state variables and 19 parameters.
2. There is, generally speaking, a lack of cheap and reliable sensors for on-line measurement of the key state variables, in particular those involved in the model. Despite considerable efforts, on-line sensor technology is still considered to be the weakest part in the real-time process control chain (Harremoës *et al.*, 1993); Vanrolleghem and Verstraete, 1993).

Both problems are common to all biotechnological processes, although particularly crucial in activated sludge processes, because of the inherent particularly complex nature of these processes, involving for instance many different microbial populations, and which, furthermore, are often difficult to reliably measure with the available instrumentation.

Because of the model complexity and the scarcity of on-line sensors, the identifiability study of the dynamical models, prior to any identification, is certainly a key question. In a previous paper (Dochain *et al.*, 1995), we have studied the structural identifiability of four kinetic models under the assumption that only oxygen uptake rate data are available. In this paper, we shall concentrate on the practical identifiability of one of these models (Single

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Monod model), and the design of optimal experiments in order to obtain the best parameter estimates possible.

While the structural identifiability is studied under the assumption of perfect (i.e. noiseless) data, the problem with highly correlated parameters arises when a limited set of experimental, noise-corrupted data is used for parameter estimation. Under such conditions the uniqueness of parameter estimates predicted by the theoretical analysis, may no longer be guaranteed, because a change in one parameter can be compensated almost completely by a proportional shift in another, still producing a satisfying fit between experimental data and model predictions. In addition, the numerical algorithms that perform the nonlinear parameter estimation show poor convergence when faced with this type of ill-conditioned optimization problems, the estimates being very sensitive to the initial parameter values given to the algorithm (Holmberg, 1982; Marsili-Libelli, 1992). Consequently, the estimated parameters may vary over a broad range and little physical interpretation can be given to the parameter values obtained.

In order to overcome the practical identifiability problem, it has been proposed to use additional *a priori* information—such as a known maximum growth rate—to impose parameter bounds (Holmberg, 1982) as mentioned in Munack (1989). Alternatively, Vialas *et al.* (1986) proposed to sample more frequently in defined periods of the experiment in order to increase the informative content of the collected data.

A few studies were directed at the design of experiments by which more informative data can be collected. In Holmberg (1982), it is shown that the practical identifiability of Monod parameters from batch experiments depends on the initial substrate concentration. The author stated that the optimal initial substrate concentration depends on the noise level and the sampling instants. It is also obvious from the results that the experimental design is dependent on the parameter values, which, in view of the changing nature of the process studied in this paper, implies that the experimental design is time-varying. In Munack (1989) different modifications are proposed to batch experiments and it is shown that important improvements in parameter confidences can be achieved by optimal experimental design techniques.

The paper is organized as follows. First, the theoretical framework of the practical identifiability study and of optimal experimental design is introduced. The paper then describes the optimal experimental designs applied to the Single Monod model which are illustrated with experimental data.

The experiments that are evaluated with respect to their information content are short-term (30 min) batch experiments, with an extension towards simple fed-batch systems (then an additional amount of sample is added in the course of the experiment). Optimal experimental designs are proposed and tested with experiments. A novel aspect of this work is that the procedures are implemented for on-line use in a respirographic biosensor installed at the treatment plant, allowing to update the parameters in the process models on-line. The so-called "In-Sensor-Experiments" performed in this respirometer are preferred over data obtained from the full-scale treatment plant since identification-in-the-loop may be subject to serious experimental constraints (with respect to excitation signals), leading to important practical identifiability problems.

2. THEORETICAL FRAMEWORK

The question addressed in this section is the following: with the available experimental data, can the parameters be given unique values, or, in other words, if a small deviation in the parameter set occurs, does this have a considerable decrease of the fit as a consequence. Mathematically, this can be formalized as follows (Munack, 1991). First let us recall that parameter estimation can be formulated as the minimization of the following quadratic objective functional by optimal choice of the parameters θ

$$J(\theta) = \sum_{i1}^{N} [y_i(\hat{\theta}) - y_i]^{\mathrm{T}} Q_i [y_i(\hat{\theta}) - y_i] \quad (1)$$

in which y_i and $y_i(\hat{\theta})$ are vectors of N measured values and model predictions at times $t_i (i = 1 \text{ to } N)$ respectively, and Q_i is a square matrix with user-supplied weighting coefficients. The expected value of the objective functional for a parameter set slightly different from the optimal one can be approximated by (Munack, 1989)

$$E[J(\theta + \delta\theta)] \cong \delta\theta^{\mathrm{T}} \left[\sum_{i1}^{N} \left(\frac{\partial y}{\partial \theta}(t_i) \right)^{\mathrm{T}} Q_i \left(\frac{\partial y}{\partial \theta}(t_i) \right) \right] \delta\theta + \sum_{i1}^{N} \mathrm{tr}(C_i Q_i) \quad (2)$$

in which C_i represents the measurement error covariance matrix (Q_i is typically chosen as C_i^{-1} or as the identity matrix). An important consequence of (2) is that in order to *optimize the practical identifiability* [i.e. maximize the difference between $J(\theta + \delta\theta)$ and $J(\theta)$] one has to *maximize the first term of the right hand side of* (2) *for given values of* $\delta\theta$. This implies that the term between brackets [·], i.e. the so-called Fisher Information Matrix, which expresses the information content of the experimental data (Ljung, 1987)

$$F = \sum_{i1}^{N} \left(\frac{\partial y}{\partial \theta}(t_i) \right)^{\mathrm{T}} Q_i \left(\frac{\partial y}{\partial \theta}(t_i) \right) \quad (3)$$

plays a central role in the optimization process. This matrix is the inverse of the parameter estimation error covariance matrix of the best linear unbiased estimator (Godfrey and DiStefano III, 1985)

$$V = F^{-1} = \left(\sum_{i1}^{N} \left(\frac{\partial y}{\partial \theta}(t_i) \right)^{\mathrm{T}} Q_i \left(\frac{\partial y}{\partial \theta}(t_i) \right) \right)^{-1}. \quad (4)$$

The approximation (2) of the objective function allows to draw lines of constant functional values in the parameter space. In case a two-parameter problem is addressed, these lines form ellipses. As it is pointed out in Munack (1989), the axes of the ellipses are given by the eigenvectors of the Fisher matrix and their lengths are proportional to the square root of the inverse of the corresponding eigenvalues. Hence, the ratio of the largest to the smallest (in absolute value) eigenvalue is a measure of the shape of the functional close to the optimal parameter estimates.

2.1. Optimal experimental design for parameter estimation (OED/PE)

Different strategies have been developed to design experiments in such a way that the measurement data allow unique determination of the (combinations of) parameters that were shown to be structurally identifiable, i.e. produce "informative" experiments. The Fisher Information Matrix or, equivalently, the covariance matrix are the cornerstones of the optimal experimental design procedures because these matrices summarize the information content of an experiment or the precision of the parameter estimates. Depending on the requirements imposed by the application different scalar measures of these matrices are optimized (Munack, 1991)

A—optimal design criterion: $\min[\mathrm{tr}(F^{-1})]$ (5)

Modified A—optimal design criterion: $\max[\mathrm{tr}(F)]$ (6)

D—optimal design criterion: $\max[\det(F)]$ (7)

E—optimal design criterion: $\max[\lambda_{\min}(F)]$ (8)

Modified E—optimal design criterion: $\min\left[\dfrac{\lambda_{\max}(F)}{\lambda_{\min}(F)}\right]$ (9)

in which $\lambda_{\min}(F)$ and $\lambda_{\max}(F)$ are the smallest and largest eigenvalue of the Fisher information matrix. The following interpretation can be given to these optimal experimental design criteria (Munack, 1991). The A- and D-optimal designs minimize the arithmetic and geometric mean of the identification errors respectively. The E-criterion based experimental designs aim at minimizing the largest error. Because in these criteria a maximization of eigenvalues of the Fisher Information matrix is pursued, they guarantee the maximization of the distance from the singular (non-informative) case. The modified E criterion should be interpreted in the frame of the objective functional shape. The ratio of the largest to the smallest eigenvalue is an indication of this shape*. When $\lambda_{\min}(F)$ is zero, this ratio is infinite, i.e. an infinite number of parameter combinations can be used to describe the experimental data and hence the experiment is non-informative. The Fisher matrix is then singular, and hence the D- and E-criteria are zero while the A-criterion cannot be determined since inversion of F is impossible. This example is also illustrative of the problems that can be encountered with the modified A-criterion: even if a non-informative and unidentifiable experiment is conducted, the modified A-criterion may still be maximized because one of the other eigenvalues has become large (Goodwin, 1987). Finally, it should be mentioned that other design criteria can be proposed, e.g. reducing the estimation error of a particular parameter can be obtained by designing experiments with this variance component as design criterion.

Designing identification experiments requires several choices, e.g. what outputs should be measured at what time instants and at what frequency, and what inputs to manipulate and in what way. In this work, the output and sampling frequency are no longer available to the experimenter since they are fixed by the hardware used in the study. The only degree of freedom left is the design of the input. Optimal experimental design therefore reduces to finding the input functions $u(t)$ that lead to the most informative experiments.

*The objective is to have eigenvalues as close as possible to each other: the shape is then circular.

Finally, it must be stressed that optimal experimental designs for nonlinear models are influenced by the parameter values since the design criteria are based on the Fisher information matrix which is parameter dependent (via $\partial y/\partial\theta$). In the application studied here this feature has considerable implications. For instance, as the wastewater/sludge interaction is time-varying, the values of the biokinetic parameters of the biodegradation are changing, and therefore the optimal experimental design has to be changed as well.

3. OPTIMAL EXPERIMENTAL DESIGN FOR THE SINGLE MONOD MODEL: INTRODUCTION

In a previous paper (Dochain *et al.*, 1995) we have studied the structural identifiability of four kinetic models (Exponential, Single Monod, Double Monod and modified IAWQ No. 1) based on $\mathrm{OUR_{ex}}$ measurements. Here we shall concentrate on the practical identifiability and the optimal experimental design for parameter estimation (OED/PE) of one of these models, the Single Monod model

$$\frac{dS_1}{dt} = -\frac{\mu_{\max 1} X}{Y_1}\frac{S_1}{K_{m1}+S_1} \quad (10)$$

$$\mathrm{OUR_{ex}} = -(1-Y_1)\frac{dS_1}{dt}. \quad (11)$$

Under the considered experimental conditions (low ratio S_1/X), the biomass growth can be neglected $[(dX/dt)=0]$, and X considered as a (constant) parameter.

The choice of the Monod model is, at least partially, motivated by its very large use in biotechnological applications, and particularly in activated sludge processes. More specifically in the context of this study, this choice means that we assume that the experimental data are characterized by Single Monod kinetics, either because the process is known to be characterized by this type of kinetics, or because a preliminary model structure discrimination has been performed, possibly by "In-Sensor Experiments" (see Vanrolleghem *et al.*, 1994), leading to the selection of the Monod kinetics.

In (Dochain *et al.*, 1995), we have shown that three combinations $[(\mu_{\max 1}X(1-Y_1))/Y_1]$, $(1-Y_1)S_1(0)$, $(1-Y_1)K_{m1})$ of the five original parameters $(\mu_{\max 1}, X, Y_1, S_1(0), K_{m1})$ are structurally identifiable. In order to have a presentation as illustrative as possible (via e.g. the use of 3-D plots of the confidence regions), we assume here that the initial substrate concentration $S_1(0)$, the yield coefficient Y_1, and the biomass concentration X are assumed to be known *a priori* (via some separate experiments). This leaves two parameters $(\mu_{\max 1}, K_{m1})$ to be estimated.

Simulation OED/PE studies have first been performed in (Vanrolleghem, 1994). The results can be summarized as follows:

- The results presented indicate that the information quality of the experiments is highly dependent on the design and that major improvements can be achieved by changing initial substrate concentrations and extending the experiments to fed-batch operation (with injection of additional substrate at an optimal time in the course of the experiments).
- It was observed that the different OED/PE criteria mentioned above yield different OED's. The constraint imposed by the desired real-time operation of the respirographic biosensor (i.e. experiments no longer than 40 min) has a significant influence: if the constraint is not considered, all but the modified E criterion would lead to prohibitively long experiments.
- A number of pulse additions higher than one further improves practical identifiability but the

benefits become marginal as the experiment complexity increases. One or two additional pulses seem worth the effort.

As a reasonable compromise of experimentation length and informative quality of the experimental data, it is proposed to design the respirographic experiments as follows. An additional pulse of substrate is injected at the time when the exogenous oxygen uptake rate is substantially decreasing, i.e. when the substrate has dropped to concentrations near to the affinity concentration. The amount of substrate at the beginning of the experiment is imposed by the allowable experimentation length.

Two examples of OED/PE, based on experimental data, will now be developed here:

1. Optimal initial substrate concentration.
2. Optimal additional pulse with fixed initial substrate concentration.

In (Vanrolleghem, 1994), other simulation examples with optimal additional pulse and initial pulse, and optimal design with multiple additional pulses are presented.

The start of a batch experiment by pulse injection of wastewater is included in the model via the initial conditions $S_1(0)$ (which will be the degree of freedom in the optimal experimental design). An additional term in the mass balance is required to describe the fed-batch experiments that are also treated in this paper. In order to prevent numerical problems, a pulse injection of wastewater in the course of an experiment is described by a Gauss-like function

$$S_{\text{puls}} \exp\left[-\frac{(t - t_{\text{puls}})^2}{\sigma}\right] \tag{12}$$

in which t_{puls} is the time instant at which the pulse is given, σ is the width of the pulse and $S_{\text{puls}}\sqrt{\pi\sigma}$ is the total amount of substrate injected.

4. EXPERIMENTAL RESULTS OF OED/PE

4.1. Introduction

The experiments used here are obtained from an on-line respirographic biosensor that performs (fed)-batch experiments automatically. Typically 30 minute records of OUR_{ex} data are produced and subjected to an identification procedure.

The two degrees of freedom (initial substrate + additional pulse) have been evaluated with the RODTOX respirographic biosensor (Kelma bvba, Niel, Belgium). Since a single Monod type model was studied, acetate was chosen as a substrate known for its Monod-type degradation characteristics. The activated sludge was obtained from the Maria Middelares treatment plant in Gent, Belgium treating municipal and hospital wastewater. Operating conditions of the bioreactor integrated in the sensor were $25.0 \pm 0.1^\circ$C, pH 7.00 ± 0.2 and dissolved oxygen above 3 mg O_2/l. All experiments were run on the same day to guarantee similar sludge characteristics between the different tests.

4.2. Reference experiment

The reference experimental OUR_{ex} profile consists of a batch experiment with an initial acetate concentration of 20 mg COD/l. Figure 1 presents the collected experimental data and the fit of the single Monod model. Since the validation work was mainly directed to the improvement of the objective functionals' shape (modified E criterion), this shape was calculated for a grid of parameter combinations $\mu_{\max 1}$, K_{m1} in the neighbourhood of the optimum (Fig. 1). It should be emphasized that the surface and corresponding contourplot depicted in Fig. 1 is the result of systematic exploration of the error functional in parameter space and is not a mere representation of the linearized objective functional around the optimum as it is often found in the literature (Lobry and Flandrois, 1991).

This example of a narrow valley in the parameter space may be the source of considerable problems to certain optimization algorithms. Experience with the cases studied so far tells that there exist adequate optimization algorithms, such as the direction set method of Brent (1973), which converge to the global minimum ($\mu_{\max 1} = 2.457\ 10^{-4}$/min; $K_{m1} = 0.456$ mg COD/l). In order to minimize numerical problems, the parameter values have been normalized during the estimation procedure. In any case, a valley is undesirable and the aim of the study was to see whether the proposed OED/PE methods would result in improved properties. Hence rescaling was not considered during the OED phase since the objective of this work is to illustrate the potential of OED techniques.

The Fisher information matrix corresponding with this experiment and the deduced values of the different OED/PE criteria are summarized

$$F = \begin{pmatrix} 3.475\ 10^8 & -12250.1 \\ -12250.1 & 0.57715 \end{pmatrix},$$

$$V = \begin{pmatrix} 1.148\ 10^{-8} & 2.443\ 10^{-4} \\ 2.443\ 10^{-4} & 6.926 \end{pmatrix} \tag{13}$$

$$\mathrm{tr}(F) = 2.005\ 10^8, \quad \det(F) = 5.03\ 10^7,$$

$$\mathrm{tr}(V) = 7.95\ 10^{-8} \tag{14}$$

$$\lambda_{\min}(F) = 0.145\ 10^{-2}, \quad \frac{\lambda_{\max}}{\lambda_{\min}}(F) = 2.39\ 10^9. \tag{15}$$

4.3. Example 1: initial substrate concentration

As a first experimental illustration, let us evaluate the effect of a change in initial concentration on the error functional shape and assess the estimation accuracy. For this purpose a batch experiment was conducted with half the initial concentration of the reference experiment (see Fig. 2). The modified E-criterion value calculated from the experimental results was 2.42 times lower than the reference value, confirming the findings of the theoretical work described above, i.e. lower substrate concentrations give rise to batch experiments in which the error functional is more cone-like. However, theoretically it was also pointed out (Vanrolleghem, 1994) that this

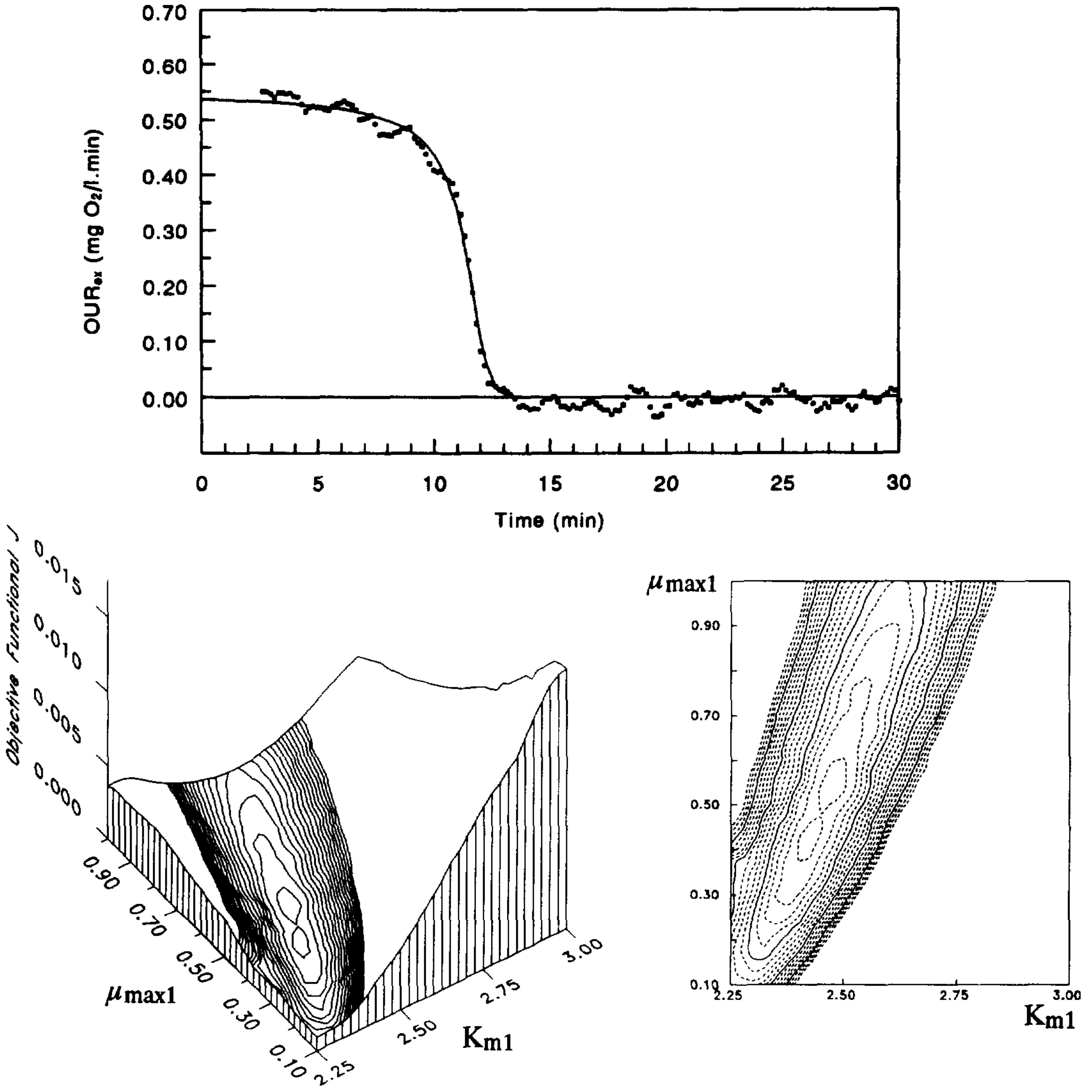

Fig. 1. 3D- (left) and contour-plot (right) of the objective function as a function of the Monod parameters for the reference respirogram (top).

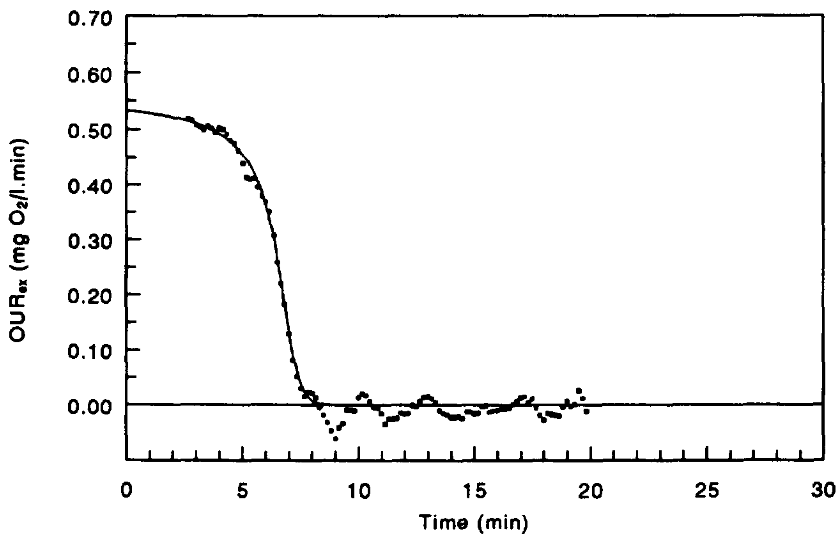

Fig. 2. Experimental respirogram in the initial substrate case.

numerical improvement was at the expense of estimation accuracy. Hence, the parameter variances were calculated and it was found that the variances had increased, especially for the μ_{max1} parameter (increased with a factor 3.82) and to a lesser extent also for the inffinity constant K_{m1} (a factor 1.52). Let us note that OED based on the modified E criterion may sacrifice parameter estimation accuracy for improved numerical properties.

The optimal designs can be computed for the characteristics of the activated sludge and substrate used in these experiments. Simulations are performed by using the model and the parameter values estimated from the previous experiment for a series of initial substrate concentration values. For each tested initial substrate concentration, the criterion values are obtained. For the D-criterion for instance, the results are shown in Fig. 3 (compare also the value of the D-criterion (max[det(F)]) in Fig. 3 and the value given in (14) for the reference experiment). The designs are indeed very similar for all but the modified E criterion. For the latter, an optimal initial substrate concentration of only 1.54 mg/l is proposed, while all other criteria point to a maximal amount of substrate (60 mg/l) as the best design.

4.4. Example 2: additional pulse

The effect of an additional pulse of substrate was examined with three experiments in which the substrate concentration in the bioreactor was increased with 2 mg COD/l. Different injection times were tested in order to illustrate the effect of an optimal t_{puls}.

Suppose first that the data of the reference example are available and that an additional experiment has to be designed with the possibility of adding one more substrate pulse. The calculations result in curves of criterion values vs injection time, summarized in Fig. 4. These graphs show the differences in optimum time for the different design criteria. The A-, D- and E-criteria propose to inject a substrate pulse after 14.6 min (after complete degradation of the initial substrate). The modified A-criterion based experiment consists of a prolonged batch-phase. And the modified E criterion OED results in a respirogram in which the oxygen uptake reaccelerates just before complete disappearance of the initial amount of substrate. Compare also the optimum values of the different criteria in Fig. 4 with the values given in (14, 15) for the reference experiment.

The three experiments that were performed had injection times of 13, 14.1, and 14.6 min respectively. The resulting OUR_{ex} profiles are given in Figs 5–7.

A first important observation is that the model structure adequately describes the experiments well. The pulse is described very well and microbial metabolism does not seem affected by the important transients imposed.

The following conclusions can be drawn by focusing on the effect of these fed-batch experiments on the error functional shape and parameter variances.

Although the expected values for the modified E criterion and the variances may change to a certain extent from the actually observed values due to changes in noise level, experimental error and also

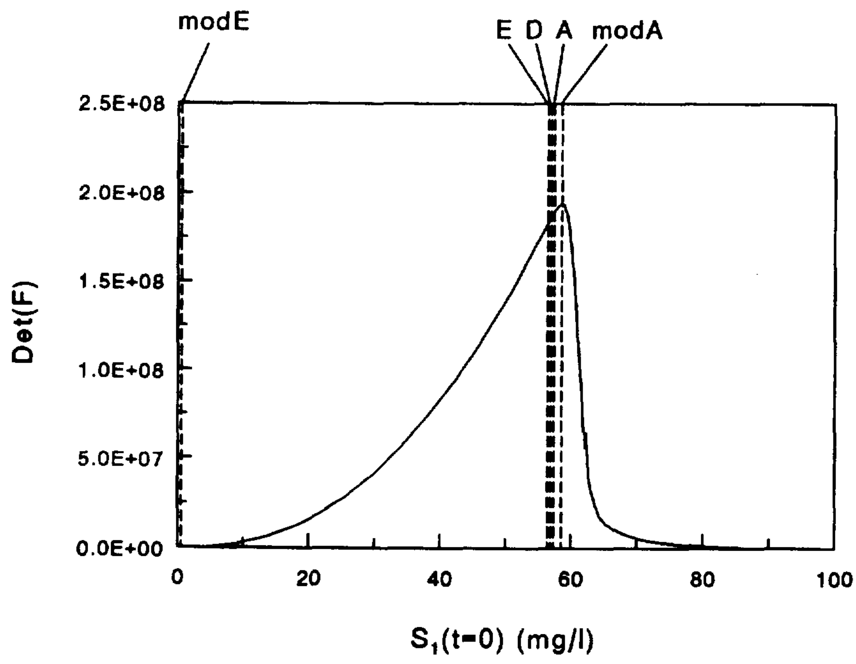

Fig. 3. Evolution of the D criterion as a function of the pulse addition time (vertical lines = optimal concentration for the different criteria).

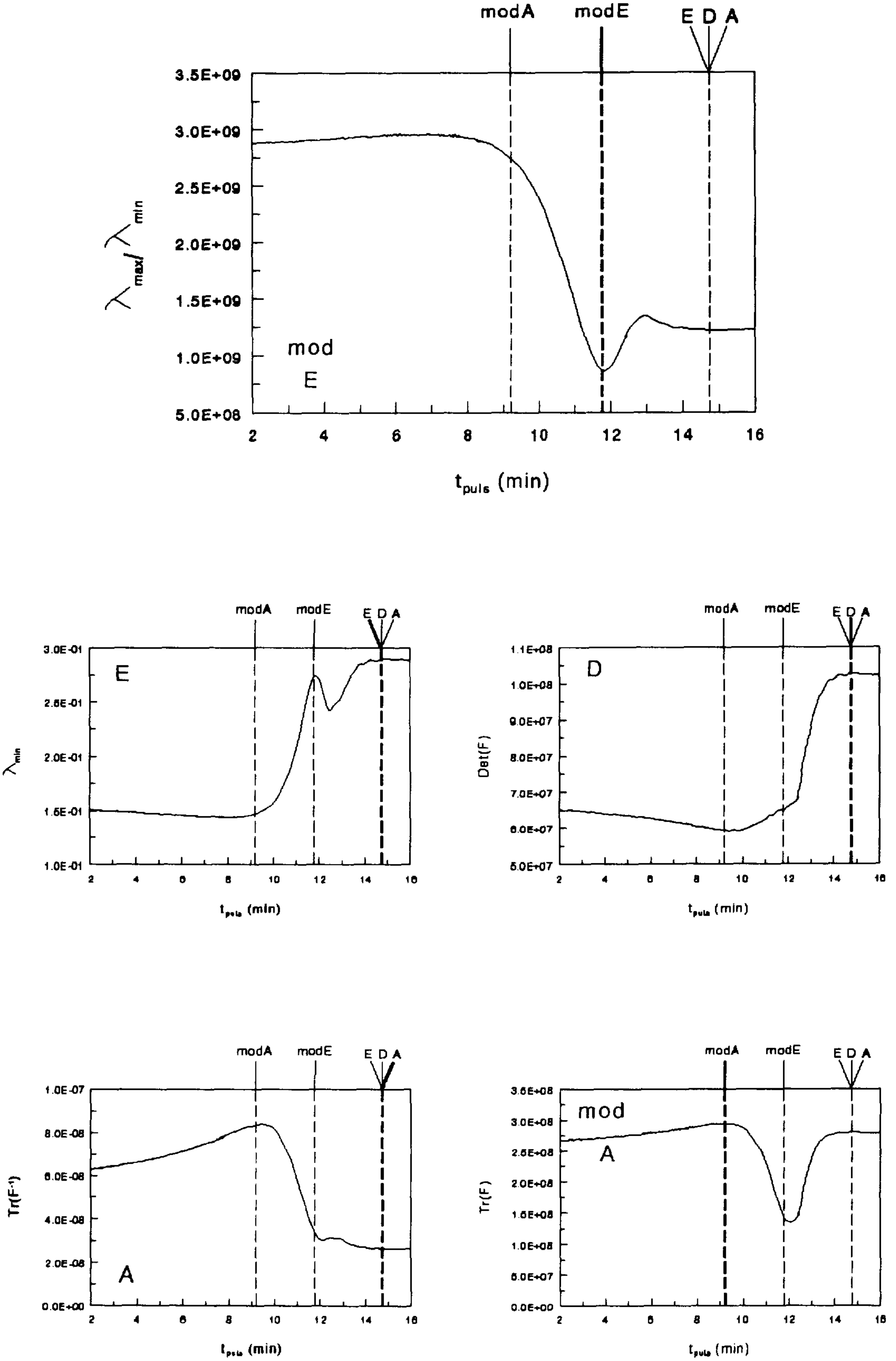

Fig. 4. Evolution of the different OED/PE criteria as a function of the pulse addition time (vertical lines = optimal time of pulse addition for the different criteria).

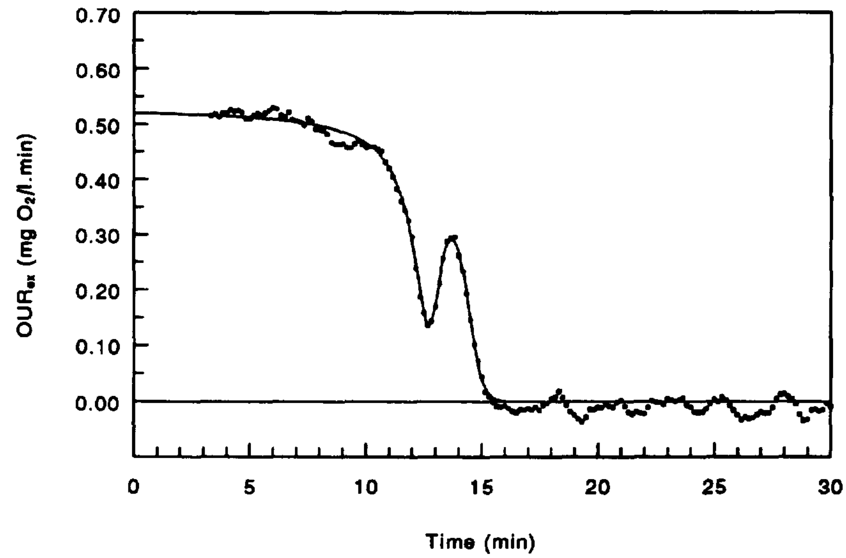

Fig. 5. Experimental respirogram obtained with a fed-batch experiment with additional pulse after 13 mins.

biological changes, the trends set by the theoretical analysis are confirmed with these results. Predicted modified E criterion values for instance were approx. 20% underestimated compared to the actual values. However, the data given in Table 1 clearly illustrate that still a significant improvement in shape of the error functional is obtained with fed-batch experiments. Moreover, as Fig. 4 illustrates, the times of pulse addition that were evaluated were in the secondary minimum for the modified E criterion and more improvement for this criterion could be achieved if substrate was injected after 11.8 min.

A second conclusion concerns the variances. The experimental results confirm that significant improvements in parameter estimation accuracy can be obtained by this small extension of the experiment.

Table 1. Dependence of the modified-E criterion and of the parameter variances with respect to the pulse addition time

t_{puls}	Modified E	Var(μ_{max1})	Var(K_{m1})	Covariance
No pulse	1	1	1	1
13	0.676	0.411	0.422	0.381
14.1	0.624	0.535	0.465	0.468
14.6	0.619	0.480	0.409	0.417

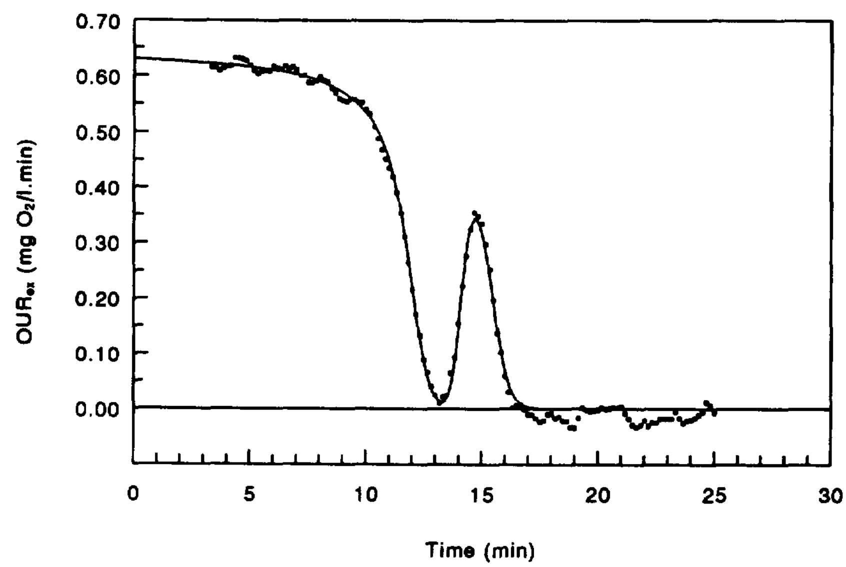

Fig. 6. Experimental respirogram obtained with a fed-batch experiment with additional pulse after 14.6 mins.

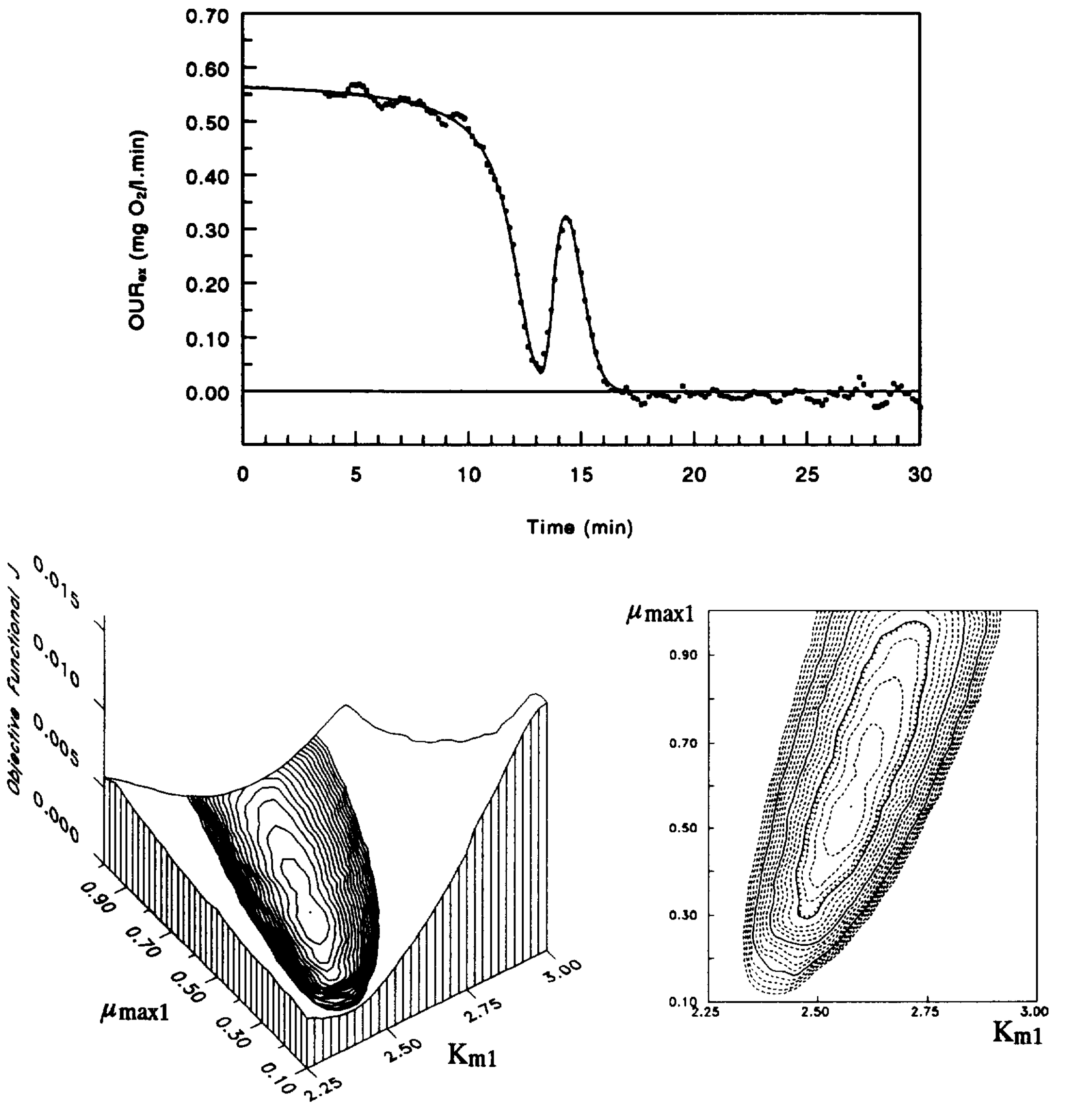

Fig. 7. 3D- (left) and contour-plot (right) of the objective function as a function of the Monod parameters for the respirogram with additional pulse after 14.1 mins (top).

The variances have decreased with more than 50% (Table 1). One should note that a similar effect can be obtained by repeating the experiment twice, but this would double the experimentation time while the approach taken here increases the experiment duration of only 3 min, i.e. 10% of normal operation.

5. CONCLUSIONS

The aim of this paper was to study the practical identifiability and the optimal experimental design of the Single Monod model in the activated sludge process. In contrast to the studies found in the literature, the analysis is not based on measurements of both biomass and substrates, but only on oxygen uptake rate data.

Optimal experimental design procedures have been applied to improve the information content of the respirographic experiments. The theoretical results were validated with experiments. The results indicated that parameter variances can be decreased by a factor two by simply modifying the usual batch-wise operation to include the injection of an additional amount of sample at an optimally chosen time instant during the experiment. The real-time constraints of sensor operation were not violated by this alternative experimental design, since the optimal experiments are only 3 min longer, corresponding to a 10% increase. It can be suggested that the optimal experimental design procedure can and probably should be performed on-line to account for the effect of parameter changes on the optimal experimental design (Vanrolleghem and Dochain, 1995). Data on X and Y (which are assumed to be known) should obviously be provided by proper analysis devices.

An interesting future research work would be the investigation of the effect on the OED of additional degrees of freedom, such as the size of the pulse addition, as well as the feeding regimes (e.g. continuous feeding).

The so-called "In-Sensor-Experiments" performed in the considered respirographic biosensor can be preferred over data obtained from the full-scale treatment plant since identification-in-the-loop may be subject to serious experimental constraints (to the excitation signals), leading to important practical identifiability problems. These constraints are non-existent when In-Sensor-Experiments are used to obtain the necessary data to feed the identification algorithm. However, it is obvious that additional data from other sensors installed at the treatment plant will complement the data needed in advanced control schemes (like adaptive linearizing control, see Bastin and Dochain, 1990).

The results described here hold for the estimation of the two biokinetic parameters of the single Monod model. A similar study can however be devoted to the other models. Let us point out that this will result in more complex optimization problems, not only for the OED but also for the parameter estimation, and that due to the nonlinear nature of the models, the parameter estimation may lead to results which correspond to local minima in the optimization procedure, i.e. to suboptimal experimental designs. This implies that here again the OED has to be carefully carried out.

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