OPTIMIZATION OF THE OPERATION OF
THE OXIDATION DITCH PROCESS
INCORPORATING A DYNAMIC MODEL

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ABSTRACT
A procedure for the optimal management of the oxidation ditch process was developed, comprising the
tegration of a dynamic process model, an input forecaster and an optimization algorithm. The system can
be set to optimize operating costs (having the effluent quality as constraint) or process performance (having a
maximum budget as constraint). Simulations with data from full scale oxidation ditches showed the
usefulness of the method in terms of on-line control and/or off-line planning. A comparison between the
proposed strategy and other conventional control policies was done by Monte Carlo simulation, varying the
values of the inputs and initial states. Statistical analysis of the results indicated that, in general, the optimal
management was able to give a significantly better effluent quality but, in some cases, at higher operating
costs.

KEYWORDS
Wastewater treatment, activated sludge, extended aeration, oxidation ditch, process model, optimal control.

INTRODUCTION
Extended aeration systems are probably the most important variant of the activated sludge process for
wastewater treatment. This popularity stems from their conceptual simplicity and the ability to perform an
efficient BOD removal, full nitrification and partial sludge stabilization. These properties result from the
large mass of solids present in the system, which are a consequence of the long solids retention time.

However, severe process failures resulting from the lack of an adequate management of these solids can be
frequently observed. The most common of these are (a) solids overloading in the final clarifiers, leading to
high effluent suspended solids and (b) reduction in the efficiency of nitrification, due to low dissolved
oxygen levels arising from the high biomass respiration. Additionally, this large solids mass also incurs a
high energy consumption for aeration, in order to supply the oxygen required for the biomass respiration. In
spite of these points, there have been so far very few attempts to control the process simultaneously
analysing both performance and operating costs.

A review of the existing control strategies for the activated sludge process, analysed in terms of their
applicability to extended aeration systems, revealed that there are virtually no attempts in adopting an
integrated view of the process management.

This paper presents a management system for the oxidation ditch process, incorporating the integration of a
dynamic process model within an optimization algorithm, which can be set to optimize performance or
operating costs. A description of the procedure is given, followed by the analysis of two applications and a comparison by Monte Carlo simulation of its efficacy compared with that of conventional operating policies.

EXISTING CONTROL STRATEGIES FOR THE ACTIVATED SLUDGE PROCESS

Introduction

The operational control of an activated sludge system can be classified according to the variables which constitute the objective of the control action. These variables can be direct measures of the quality of the effluent, or can be states or indicators that indirectly reflect the performance of the process:

(a) control of effluent quality (eg effluent BOD, effluent nitrogen)
(b) control of dissolved oxygen (eg conventional, self-tuning, DO profile)
(c) control of process indicators (eg F/M ratio, sludge age, Oxygen Utilization Rate - OUR)
(d) solids management (eg MLSS concentration, sludge mass)
(e) integrated management of performance and costs

In the activated sludge process, there are basically three manipulated variables which can be varied in order to control the system: return sludge flow ($Q_r$), surplus sludge flow ($Q_w$) and aeration level ($K_{L,a}$).

Limitations of the Existing Strategies for Application to Extended Aeration Systems

A general appraisal of the various existing control strategies, directed towards their applicability to extended aeration systems, leads to the following points:

(1) The vast majority of strategies reported in the literature are oriented towards the control of conventional activated sludge systems. Few studies have been devoted to extended aeration plants, with their particular features, such as: (a) long solids retention time, (b) high efficiency in soluble BOD removal, (c) large mass of solids kept in the system, (d) oxygen consumption dominated by biomass respiration, (e) great damping effect and resistance to shock loads, (f) high inertia against rapid changes in MLSS concentration due to manipulations of $Q_r$ and $Q_w$.

(2) Most of the operating policies do not take into account the truly dynamic conditions in the system. For instance, use of some process indicators such as sludge age in a dynamic environment leads to a mismatch between sludge production and wastage. Additionally, transients in the concentrations of limiting factors such as DO can lead to the autotrophs having a completely different sludge age from the biomass, measured by total solids. With respect to the final clarifiers, non-recognition of their dynamic nature and the accumulation terms in the mass balance can lead to erroneous predictions of the biomass concentration in the reactor, thus affecting indirectly the estimation of substrate removal and oxygen consumption.

(3) The control of the aeration tank is not usually integrated with the final clarifier. No inclusion of the latter on the control strategy can lead to serious failures in terms of effluent suspended solids and BOD (particulate fraction).

(4) The manipulated variables $Q_r$ and $Q_w$ are in many cases not varied simultaneously.

(5) The majority of studies adopt single variables (eg BOD, ammonia or DO) or process indicators (F/M ratio, sludge age or OUR) as control signals. A single signal cannot represent the operation of both the reactor and the clarifier, and also the dual objective of removal of carbonaceous and nitrogenous matter.
Optimization of the oxidation ditch process

(6) Frequently the control strategies are based on fixed set points vaguely or heuristically established for a particular state variable (such as DO or MLSS) and not for the output variables, which really define the effluent quality.

(7) Only a few strategies include reduction of operating costs as an additional objective.

(8) Many studies include only a very limited period of data (frequently only 24 hours) obtained under specific operating conditions. Analysis of the response of the system to the control strategy under different input and operating conditions is usually not attempted.

Proposed Approach

From the analysis of the above points, it was felt that there is still a need of studies on the control of oxidation ditches, in which the approach of a fully integrated management is adopted. This overall integration should comprise:

(1) Simultaneous actuation on the manipulated variables, proper consideration of the interactions between the reactor and clarifiers, and incorporation of cost reduction as one of the objectives.

(2) Operation explicitly directed towards the compliance of the output variables to set discharge standards (or targets).

(3) Use of a dynamic model of the overall system, with all the relevant input, state and manipulated variables interacting. The model, and not a single variable or process indicator, is to be used for the derivation of the control strategy.

(4) Use of optimization techniques in order to derive the settings of the manipulated variables \( Q_r, Q_w, K_{La} \) that could lead to optimal control in terms of performance or operating costs.

(5) Investigation and assessment of the proposed strategy under a large number of different conditions, in such a way as to incorporate a statistical analysis of the interpretation of the results.

OPTIMAL MANAGEMENT OF THE OXIDATION DITCH PROCESS

Introduction

The basic principle of the initial approach relates to the management of solids in the system by manipulation of the variables \( Q_r \) and \( Q_w \). The concept was subsequently expanded to include also the selection of the DO set point or aeration level.

The term 'optimal' refers to the selection of the settings of the manipulated variables based on an optimization algorithm, which can be adjusted in order to optimize the operating costs or process performance. In the case where costs are to be minimized, the plant has to satisfy the constraints imposed by the discharge standards. If, however, the effluent concentrations of specific determinands are to be minimized, maximum limits for operating costs can be stipulated. In the selection procedure of the optimal settings of \( Q_r \) and \( Q_w \), the dynamic model of the process is driven by forecast input variables and is incorporated into the optimization algorithm. These basic concepts are presented in Figure 1.

Description of the Optimal Management Procedure

Dynamic model. The dynamic model comprises the ditch (oxidation of carbonaceous and nitrogenous matter) and the final clarifier (thickening and clarification). Since the model was primarily intended for control purposes, all the input variables (inflow, influent suspended solids, influent ammonia), manipulated
variables \((Q_p, Q_w, K_{La})\) and state variables (MLSS, RASS, DO, sludge blanket height, effluent ammonia and effluent SS) are measurable on a continuous basis.

**OPTIMAL MANAGEMENT**

![Diagram of optimal management process]

**Fig. 1.** Main stages in the procedure for the 'Optimal Management of the Oxidation Ditch Process'.

The model structure of the reactor could be simplified by the consideration of the following particular characteristics of oxidation ditches (von Sperling and Lumbers, 1989): (a) biomass net growth is small and was assumed as constant; (b) the kinetics of the removal of soluble BOD need not modelled (soluble BOD close to zero); (c) the rate of oxygen consumption for the oxidation of substrate was expressed as a function of the influent BOD load (itself a function of influent suspended solids); (d) the Monod term for inhibition of nitrification by low DO was raised to a power greater than one, in order to increase its sensitivity (loss and recovery of nitrification were observed to be much faster than predicted by a Monod function). In the final clarifier the sludge zone (variable volume and concentration) was modelled dynamically, using principles of the solids flux theory, and the effluent SS were calculated from an empirical function of the sludge blanket height.

The model was calibrated with data from a full scale oxidation ditch (Carrousel system, 50000 inhabitants) and validated with four independent sets of data from other two ditches in UK (one Carrousel, one conventional Pasveer ditch). Details about the model structure, parameter estimation and simulation results can be found in von Sperling (1990).

**Forecasting of the input variables.** The proposed algorithm for Optimal Management is based on the modelling of the trajectory of the states over a specified horizon, with a further selection of the trajectory that leads to the optimal costs or performance. In order to achieve this, the input variables have to be forecast over this time period which, in the present case, is equal to 24 hours. The forecasting function is based on an ARIMA - Auto Regressive Integrated Moving Average (Box and Jenkins, 1970) model. The parameter estimation is done using Recursive Least Squares.

**Optimization algorithm.** The algorithm selected for the optimization is the Complex method for multivariable non-linear constrained optimization (Box, 1965). The objective function to be minimized is either the effluent load of ammonia and suspended solids (when optimizing performance) or the daily running costs - aeration, return sludge pumping and sludge disposal (when optimizing costs). Two types of constraints are incorporated, and the ability of easily handling both is an important feature of the algorithm developed:

(a) Explicit constraints: minimum and maximum values of the manipulated (decision) variables \(Q_p, Q_w\) and \(K_{La}\), dictated simply by physical limitations.
Optimization of the oxidation ditch process

(b) Implicit constraints: maximum values of the effluent suspended solids and ammonia concentrations (when optimizing costs) or the daily running costs (when optimizing performance). The implicit constraints are calculated from the process model, which is integrated within the optimization algorithm. By doing so, the model can be used in its original form, without any need for transformations or linearizations, which is a limitation from many optimal control strategies. A model of any complexity (e.g., IAWPRC model) can be incorporated into the algorithm, preserving its original form. The specification of the implicit constraints related to the effluent quality is straightforward, and is purely a function of the effluent standards. Therefore, there is no need for establishing questionable set points for the state variables (e.g., MLSS) or process indicators (e.g., F/M ratio, sludge age or OUR). The dynamic model calculates the expected effluent quality arising from the combined actuation of all the manipulated variables and the resulting consequences in both the reactor and final clarifier. Again, this is judged to be an advancement over previous strategies, which do not incorporate an integrated view of the process and do not control the system directly in terms of the effluent quality.

Optimization procedure. The flowchart of the optimization procedure is shown on Figure 2. Recognizing that the response of the system to changes in the manipulated variables has different time constants, the optimization is run at two stages. The first stage (short term) aims at calculating the optimal settings of $Q_r$ and $K_{La}$ for the next 24 hours. The second stage (medium term) assumes that the input variables are repeated cyclically for the next five days, and it then concentrates on the determination of the optimal value of $Q_w$ that satisfies the constraints over the next five days. This is an important characteristic of the proposed method, because it takes into account the fact that the system has a much slower response to changes in $Q_{wo}$ and that the optimal settings for the short term (one day) are not necessarily the best for a longer time horizon (five days). The second stage is limited to five days only because of the difficulties and uncertainties associated with forecasting the input variables over a longer period.

At Stage 1, the first step is the forecasting of the input variables for the next 24 hours. After that, the algorithm generates random values of the manipulated variables ($Q_r, Q_w, K_{La}$) and checks whether they satisfy the explicit constraints (minimum and maximum values). If the conditions are satisfied, the algorithm verifies the compliance to the implicit constraints (two-hourly effluent suspended solids and ammonia, or daily running costs). In order to do this, the algorithm calls the process model, which is run for the next 24 hours. If the implicit constraints are satisfied, another set of manipulated variables is generated according to the Complex algorithm. This set will pass through the same steps of compliance assessment. For each set of manipulated variables the objective function (effluent quality or costs) is calculated (also by the model) and those variables leading to a lower value are successively selected, until convergence is achieved (minimum of the objective function is found). When the constraints are not satisfied, another set of variables is generated according to the Complex algorithm. When convergence of Stage 1 is achieved, the optimal values of $Q_r$ and $K_{La}$ are adopted, and the procedure moves into the second stage, in order to find the optimal $Q_w$. This stage is structurally similar to the first, with the exception that the model is run for five days, so that the implicit constraints must be satisfied over this whole period.

In both stages, if the system is trying to optimize costs and no feasible solution can be found, the algorithm automatically shifts into optimizing performance for that specific day. This comes from the fact that priority should always be given to the effluent quality, and excursions above the limits should receive a remedial action as soon as possible.

Applications of the Optimal Management

Case study 1. Synthetic input data having the same statistical properties as the original series were generated for the large Carrousel ditch, and were used to drive the Optimal Management program. In this plant, the critical variable is effluent suspended solids, due to a solids overloading resulting from the limited sludge surplussing capacity. The constraint for effluent suspended solids was set equal to 30 mg/l, corresponding to the operating target (actual effluent standards are 60 mg/l, expressed as 95 percentiles). Figure 3 shows the effluent suspended solids simulated over a period of 20 days, under the options of optimizing COST and PERFORMANCE. It can be seen that, when optimizing COST, the daily averages of effluent SS approach...
the target value of 30 mg/l, since this corresponds to the cheapest operation (keep $Q_w$ and the sludge disposal costs as low as possible). When optimizing PERFORMANCE, the effluent concentrations are, as expected, much lower.

**OPTIMAL MANAGEMENT PROCEDURE**

**STAGE 1**
Horizon: short term (24 hours)
Decision variables: $Q_r$ and $K_{La}$

Forecast input variables (24 hours)
(flow, SS, ammonia)

Generate values of $Q_r$, $Q_w$, $K_{La}$

Explicit constraints satisfied?

- Yes, stop
- No, go to OPTIM. COST

**OPTIM. COST**
Objective function: daily cost
Implicit constraints: max. eff.SS/ammonia

Are there feasible solutions?

- Yes, stop
- No, go to OPTIM. PERFORMANCE

Implicit constraints satisfied?

- Yes, stop
- No, go to OPTIM. COST

Current value smaller than current minimum?

- Yes, stop
- No, go to OPTIM. PERFORMANCE

Convergence achieved?

- Yes, stop
- No, go to OPTIM. COST

Optimal $Q_r$ and $K_{La}$

**STAGE 2**
Horizon: medium term (5 days)
Decision variable: $Q_w$

Keep input variables the same (5 days)

Adopt optimal $Q_r$ and $K_{La}$

Generate values of $Q_w$

Same steps as STAGE 1 (for 5 days)
Optim. COST or PERFORMANCE

Adopt optimal $Q_r$, $Q_w$ and $K_{La}$

**Case study 2.** The second example relates to the Pasveer ditch, in which the main operational problem was the poor nitrification resulting from an insufficient aeration. Using the actual input variables measured over a period of five days, the Optimal Management was set to optimize COST, and the results of the simulation were compared with the base case (original control by timer). In this example, the three decision variables were $Q_r$, $Q_w$ and the on-off range of the DO controller (on-off feedback control). Figure 4.a shows the simulated values of effluent ammonia, which indicate that the Optimal Management was able to lead to...
much lower concentrations than the original operating mode. Figure 4.b compares the numbers of aerators to be running between the two alternatives. The original operation was basically set to have two aerators running from 7:00 to 20:00, and only one aerator on the remaining hours. However, the Optimal Management suggested that a better setting would be to have three aerators running for most of the time, and only from around 4:00 to 10:00 am to decrease the number to two (the sharp drop on Day 3 was due to a power failure). Therefore, a shorter and delayed ‘off’ period was proposed. This analysis also indicates that the Optimal Management can be useful on an off-line planning mode, assisting the operator in the selection of the settings of the manipulated variables.

![Graph](https://iwaponline.com/wst/article-pdf/24/6/225/116981/225.pdf)

**Fig. 3.** Optimization of COST and PERFORMANCE. Effluent suspended solids (daily averages).

![Graph](https://iwaponline.com/wst/article-pdf/24/6/225/116981/225.pdf)

**Fig. 4.** Comparison between the original and the Optimal Management strategies. (a) Effluent ammonia; (b) Number of aerators running.

### Comparison Between the Optimal Management and Other Control Strategies

In order to assess the relative efficacy of the Optimal Management compared to other control strategies, a series of Monte Carlo simulations was carried out for the Carrousel plant. The reason for using Monte Carlo simulations was to undertake the investigations over a large number of different conditions, generated on a random basis, thus giving a statistical meaning to the results and avoiding drawing conclusions based only on pre-selected cases. This analysis concentrated on the solids management in the system. Therefore, only $Q_t$ and $Q_w$ were included as manipulated variables, and it was assumed that all alternatives had a perfect DO control. The control strategies analysed are presented in Table 1.

The feedback was of a simple type (proportional feedback), with a control interval of 24 hours, thus compatible with the planning horizon of the Optimal Management. The values of the set points and proportional coefficients were mostly obtained by trial and error, with the values selected leading to good and stable performances. Additional details can be found in von Sperling (1990).

The results from 100 runs of twenty days each, varying the input variables and the initial values of the states, are presented in Table 2. Other analyses were carried out, varying the number of days in the simulation, the
effluent quality constraints and the amplitude of the variability of the random component, all of them leading to similar conclusions. The results from these other analyses can be found at the above reference.

**TABLE 1. Control Strategies Analysed in the Monte Carlo Simulations**

<table>
<thead>
<tr>
<th>Strategy</th>
<th>$Q^*_1$</th>
<th>$Q^*_2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Fixed rate (equal to max.)</td>
<td>Fixed rate (equal to max.)</td>
</tr>
<tr>
<td>2</td>
<td>Fixed rate (equal to max.)</td>
<td>Control by SRT (17 days) (reactor + clarifier)</td>
</tr>
<tr>
<td>3</td>
<td>Feedback with sludge blanket height</td>
<td>Feedback with MLSS concentration</td>
</tr>
<tr>
<td>4</td>
<td>Feedback with mass of solids in reactor</td>
<td>Feedback with total solids mass (reactor + clarifier)</td>
</tr>
<tr>
<td>5</td>
<td>Feedback with sludge blanket height</td>
<td>Feedback with total solids mass (reactor + clarifier)</td>
</tr>
</tbody>
</table>

**TABLE 2. Results of the Monte Carlo simulations**

<table>
<thead>
<tr>
<th>Strategy</th>
<th>Effluent SS</th>
<th>Effluent ammonia-N</th>
<th>Daily average costs (pounds)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average (mg/l)</td>
<td>% within target</td>
<td>% within standard</td>
</tr>
<tr>
<td>1</td>
<td>8</td>
<td>100</td>
<td>100</td>
</tr>
<tr>
<td>2</td>
<td>27</td>
<td>70</td>
<td>95</td>
</tr>
<tr>
<td>3</td>
<td>41</td>
<td>70</td>
<td>81</td>
</tr>
<tr>
<td>4</td>
<td>20</td>
<td>84</td>
<td>98</td>
</tr>
<tr>
<td>5</td>
<td>19</td>
<td>85</td>
<td>98</td>
</tr>
<tr>
<td>Optim.COST</td>
<td>22</td>
<td>93</td>
<td>100</td>
</tr>
</tbody>
</table>

Obs.: Effluent SS: target = 30 mg/l; standard = 60 mg/l Effluent ammonia-N: target = 7 mg/l; standard = 20 mg/l.

It can be seen that, in general, the Optimal Management was able to provide the best performance in terms of effluent suspended solids, measured by the average concentration, percentage of two-hourly values within the target and percentage of two-hourly values within the standard. The exception was Strategy 1, which led to the overall best performance. However, the operating costs of this alternative were 40% more expensive than the Optimal Management, and this refinement in effluent quality is questionable, given the already high performance of the Optimal Management. The efficacy of the other strategies was poorer, with a lower compliance to targets and standards. In terms of effluent ammonia, all alternatives behaved similarly and efficiently (the critical variable in this plant is effluent SS and not ammonia). Comparing the total costs, it is apparent that some strategies are cheaper than the Optimal Management, but the relative economy does not seem high enough to justify the deterioration in the performance.

Statistical analysis based on the matched-pairs hypothesis test confirmed these points, indicating, at a 5% significance level, that:

(a) The effluent quality from the Optimal Management was significantly better than Strategies 2, 3, 4 and 5 and significantly worse than Strategy 1;
(b) The operating costs from the Optimal Management were significantly lower than Strategies 1, 4 and 5 and significantly higher than Strategies 2 and 3.
CONCLUSIONS

(1) The method is fully integrated in terms of process units (reactor and clarifier), process variables (input, manipulated and state variables), performance objectives (output variables and consent targets/standards) and operating objectives (effluent quality and operating costs).

(2) The method allows flexibility in the definition of its objectives: the operation can be directed towards the optimization of costs and performance, and the associated constraints (operating targets) can be easily modified.

(3) The requirements in terms of instrumentation for measurement of the input, manipulated and state variables are relatively intensive. Studies are being done aiming at investigating the possibility of reducing these requirements. However, if the Optimal Management is used at an off-line planning mode, hardware requirements are substantially reduced.

(4) The effectiveness of the proposed Optimal Management strategy is dependent upon the quality of the forecasting of the input variables. The forecasting method adopted in the study can be improved if additional data of different nature (e.g. rainfall data) are incorporated into the model.

(5) Compared with other control strategies, the Optimal Management was, in general, able to give a significantly better effluent quality. However, in some cases this incurred higher operating costs.

(6) The results obtained highlighted the importance of implementing operational control at oxidation ditches. The traditional concept that ditches should by principle deserve little operational attention should be re-evaluated, in order to include the need of assessing the relative benefits to be obtained by implementing operational control, in terms of a more efficient and cost effective performance.

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