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# COMPARISON OF TWO ADVANCED CONTROL STRATEGIES FOR MONITORING OF ACTIVATED SLUDGE PROCESSES

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Abstract: : This paper deals with the comparison between two control strategies for the optimal operation of Activated Sludge Processes (ASPs). The first approach describes an industrial control strategy composed of two decentralized Proportional Integral controllers (PIs) while the second approach is based on a state space model of the system together with the Disturbance Modeling Principle (Johnson, 1976). It is shown that if the second approach needs additional sensors than the first one, when implemented properly, it allows the user to estimate unknown inputs that can be useful for diagnosis purposes. Simulation results are provided before some conclusions are drawn. *Copyright © 2002 IFAC.*

Keywords: biotechnology, control, disturbance rejection, estimation.

## 1.- INTRODUCTION

The Activated Sludge Process is a widely used system for biological wastewater treatment. Traditionally, ASP's involve an anoxic followed by an aerobic zone and a settler from which the major part of the biomass is recycled to the anoxic bassin. This prevents washout of the process by decoupling the Sludge Retention Time (SRT) from the Hydraulic Retention Time (HRT).

As it is underlined in (Lukasse et al., 1999), the main challenge in control of the ASP's can be posed in terms of a disturbance attenuation control problem. Furthermore, the problem faced is a multivariable nonlinear control problem of time varying ill defined systems. A comprehensive view of the problems involved in these processes is summarized in (Andrews, 1994).

Among the specific problems to be solved, the following ones are of first order :

- Attenuation of the bad influence of rain events on the controlled variables,
- Accounting for the large range of variations of ASP's internal dynamics,
- Attenuation of the bad influences of the influent charateristics and flows rates diurnal variations.

The main improvement to be expected is the minimization of cost operation and management by controlling the process through its control handles. In this study, the control inputs are the aeration power in one of the aerobic tank and the internal recirculation flow rate. This paper is organized as follows. In section 2, the benchmark model is recalled. Then, the PI control strategy is described in section 3. In section 4, the state space approach is presented. Then, results are discussed in section 5 before some conclusions are drawn in section 6.

## 2.- A BENCHMARK FOR EVALUATING CONTROL STRATEGIES IN ASPS

### *2.1.- Description of the benchmark*

The COST Action 682 (now being called COST Action 624) is dedicated to the optimization and to the evaluation of the design and the operation of biological wastewater treatment processes on the basis of process dynamical models. In this project, a first benchmark (now being updated within the framework of COST Action 624) was developed in order to evaluate control strategies on a common and independent basis (Pons et al., 1999). This first benchmark consists of a fully specified model of a predenitrification type activated sludge plant. The layout of this activated sludge plant is illustrated in Figure 1. It consists of two anoxic completely mixed tank compartments, followed by four completely mixed aerobic tanks. The first three aerobic tanks are subject to a constant aeration flow, while the aeration of the last aerobic compartment is variable. An internal recycle flow links the last tank to the first anoxic compartment, which also receives the influent and the recycled sludge from the settler. The influent composition and flow rate are fully specified. In this paper, only the dry weather files are used. The waste sludge flow rate and recycle sludge flow rate are set at a fixed value, while the internal recycle flow is variable and used as one of the two control actions.

The model used in this first version of the benchmark is the association of the ASM 1 model (Henze et al., 1987) with the Takacs model (Takacs et al., 1991) for simulating the settler behavior. The parameter values and an initialization procedure for the states are specified. The following measurements are assumed to be available : a perfect measurement of the oxygen concentration in the 2nd compartment and a discontinuous biased measurement of the nitrate concentration in the 6th compartment, the noise on this measurement being provided with the benchmark. The sample period of this measurement is 20 minutes. The control tasks to be performed on this benchmark are to maintain the $NO_3$ concentration in the 2nd compartment at 1 mg/l and the oxygen concentration in the 6th compartment at 2 mg/l.

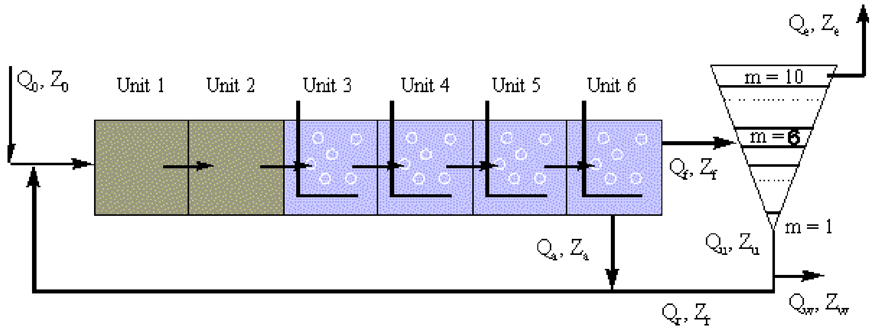


***Figure 1 :*** *Illustration of the COST 682 benchmark No. 1*

*2.2.- Implementation of the benchmark*

The benchmark is implemented using SIMBA 3.0 + (IFAK, 1998), an application for the MATLAB Simulink (The Mathworks, 1998) environment. Since the benchmark makes use of the same models as SIMBA, (i.e., the ASM 1 model and the Takacs settler model), the implementation was only a matter of parametrization. The hydraulics model used in the standard SIMBA blocks however deviated somewhat from the model used in the benchmark, where the hydraulic dynamics of the various tanks is not taken into account. Setting these dynamics very fast however, yields to the fact that the benchmark was approximated in a satisfactory manner.

*2.3.- Modeling approaches*

It is to be noticed that the previously presented benchmark model has to be seen as a simulation model (also called an evaluation model). In other words, this benchmark model is used to simulate the real behavior of the process variables and then, the control designer is assumed to face a real process. As a consequence, he does not know, a priori, the number of real biological states involved neither the expressions of the kinetics, etc… He can only use this model to generate some relevant data in order to obtain a design model that will be used for control synthesis.

When choosing this approach, two solutions are then offered to the control designer who absolutely needs a model. On the one hand, he can identify the process using an input-output description. This refers to black box or behavioral modeling. On the other hand, he can re-model the process in assuming a reaction network and in setting expressions for kinetics to obtain an internal nonlinear description of the process (knowledge or white box modeling). Obviously, in this second case, it is necessary to get a number of internal pertinent biological data that are usually very difficult to obtain regarding the limited number of available measurements. In this paper, the process is modeled using a black box modeling approach. Furthermore, up to now and to prevent confusion about the models under interest, the box that simulates the behavior of the actual plant is either called the "simulation model", "the plant" or "the actual plant"...

In the following, two control strategies are investigated. The controllers are synthezised using two specific design models which the identification is explained in details and these control laws are tested in simulation using the simulation model.

## 3.- TWO INDEPENDENT PI CONTROLLERS

### *3.1.- Structure of the control*

In a first approach, we chose to control the nitrate concentration by manipulation of the internal recycle flow rate, and the oxygen by manipulation of the $K_{la}$, with two independent PI controllers. In order to tune the two PI controllers independently, two black box SISO models were constructed for each of the two identified subsystems.

### *3.2.- System identification*

In order to facilitate the implementation and the burden on the plant, the necessary experiments that have to be performed in reality in order to identify these models were deliberately kept simple. The experiments consist of two step changes on the actuators (a change in $Kla$ from 3.5 to 6 $h^{-1}$ and a change in $Q_a$ from 18444 to 36888 $m^3/d$). For each of the considered subsystems, a first order plus pure time delay model was selected for its simplicity. It was found that the disturbances (imposed by the influent variations) had a very important influence on the system responses. Therefore a model for the disturbances were also considered. For each of the considered subsystems, the model chosen for the disturbances was a double sine wave superposed on the output of the first order plus delay.

The unique model structure was thus the following :

$$y_1 = f_1(u) + w(t) \qquad (1a)$$

$$y_2 = f_2(u) + w(t) \qquad (1b)$$

with $f_1$ and $f_2$ the first order plus delay models, and $w$ the double sine wave :

$$w(t) = A_1 \sin(2pt + j - \frac{p}{2}) + A_2 \sin(2pt + j) \qquad (2)$$

Because of lack of space, the results of the identification are not presented here

### *3.3.- The control design*

These simple models were then used to optimize the parameters of two independent PI controllers. The objective functions to be minimized were the Integral Absolute Error (IAE) of the errors between the constant setpoints and the responses of the models simulated over 20 days. The values that resulted from this optimization were then used in the PI controllers on the plant (the simulation model).

### *3.4.- Experimental results*

In order to be applied to the plant in the more possible realistic conditions, the previously synthesized controllers were discretized using first order Euler approximations of the control laws and applied to the simulation model. The results of one 14 dry weather run, compared to the non controlled case, are shown in Figures 2

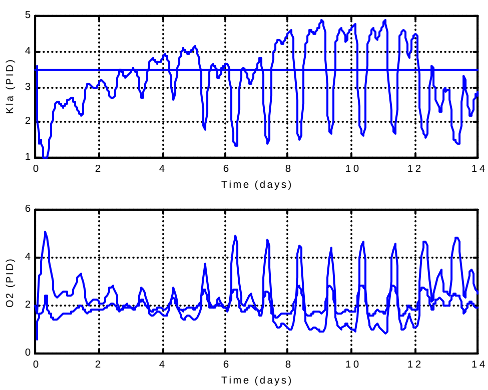


***Figure 2a :*** *Plant results of independently optimized PI controllers : $Kl_a$ / $O_2$*

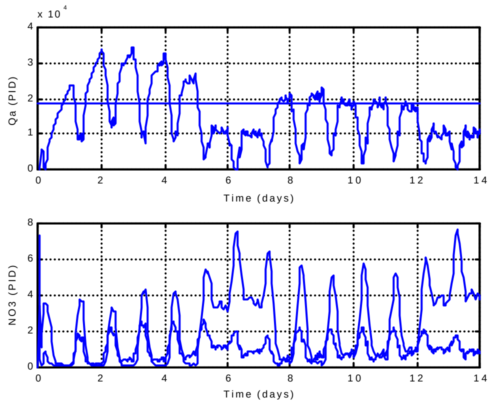


***Figure 2b :*** *Plant results of independently optimized PI controllers : $Q_a$ / $NO_3$*

Before discussing these results in details, the following section presents the second control approach.

## 4.- A DISTURBANCE ACCOMMODATING CONTROLLER

### *4.1.- The control strategy*

In (Skelton, 1989), disturbances are classified into two classes : noises and waveform perturbations and, for this last kind of disturbances, Johnson (1976) has developed the Disturbance Accommodating Control theory (DAC) that uses the so-called Disturbance Modeling Principle (DMP). Mathematically speaking, this concept consists of assuming that any disturbance signal is a linear combination of different basic functions : constants, ramps, sine or polynoms. In fact, this concept is very similar to the approach we used previously. However, as it will be shown hereafter, its use within an advanced optimal control strategy leads us to consider the state space form of the disturbance model instead of considering its nonlinear form as written in equation (2). When the disturbances are modeled by these mathematical functions under a state space form, the model of the process can be augmented by the model of the disturbances. Notice however that the higher the degree of the disturbance model, the higher the degree of the controller. Then, under appropriate observability hypothesis, the use of a state estimator such as a Kalman filter allows us to estimate on line the process state together with the expected disturbances without actually measuring them. Notice that if the disturbances vary with time, this strategy holds if the dynamics of the estimator are faster than those of the disturbances.

This theory was motivated by the fact that in most of the practical applications, the experts or the engineers in charge of the process have an *a priori* idea about the kind of internal/external disturbances they can expect to deal with. More precisely, in this paper, the structure of the disturbances to be rejected is well known (very close to the double sine previously considered). Using this approach, the control problem can then be seen as an unmeasured input disturbance attenuation problem (i.e., the input ammoniac and COD concentrations, the latest being defined as a function of the state in the benchmark).

Because of lack of space, the design procedure is not detailed in this paper. However, it follows the classical procedure proposed in (Johnson, 1976).

*4.2.- System identification*

The process to be characterized is a Multi Input Multi Output system (MIMO). In order to find a linear model of this system, the process was stabilized around a functioning point. At that point, it was assumed that both the input and output ammonium concentrations together with the input COD, the nitrate concentrations in the 2$^{nd}$ reactor and the oxygen concentration in the 6$^{th}$ tank were measured. However, it is to be noticed that these assumptions are only necessary during the time required to get data to be used for system identification. Once identified, we will only use the actual measurements that are the nitrate concentration in the 2$^{nd}$ reactor and the oxygen concentration in the 6$^{th}$ tank.

To identify the links between the outputs and the inputs, the process was excited with negative and positive input steps of about 10 l/h magnitude over 6 series of 200 hours each around the predefined functioning point. The sampling period was 20 minutes. The best data fit for the series has been retained and are not shown here because of lack of space.

The data set used for identification have been introduced into the well known algorithms from the Matlab® Identification Toolbox software (see (Ljung, 1995) following the standard procedure proposed by Ljung (1987).

The best least square approximation has been found by a systematic trials and errors procedure (including the choice of the structure and of the degree of the model). The model was then transformed into a discrete state space form and then augmented by the model of the disturbance as proposed in (Johnson, 1976).

*4.3.- The control design*

An optimal Disturbance Accommodating Control law based on this augmented model was synthesized using the well known Linear Quadratic Gaussian (LQG) controller design.

*4.4.- Experimental results*

The conditions for the implementation of the DAC were the same than those used for the PI controller. The results of two different tunings of the DAC (choice of the weighting matrices $Q$ and $R$) are shown in Figure 3 and 4 together with the open loop simulations :

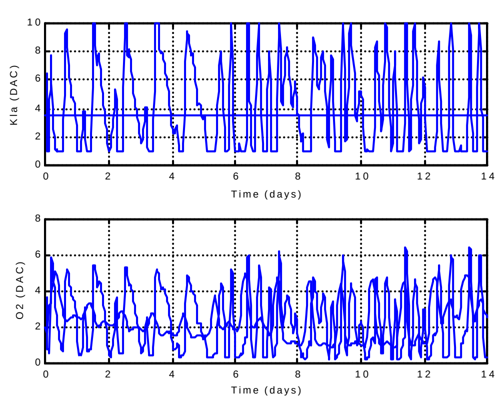


***Figure 3a :*** *Plant results using DAC #1 : $Kl_a$ / $O_2$*

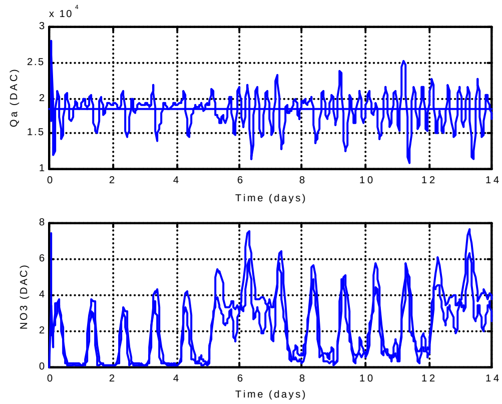


***Figure 3b :*** *Plant results using DAC #1 : $Q_a$ / $NO_3$*

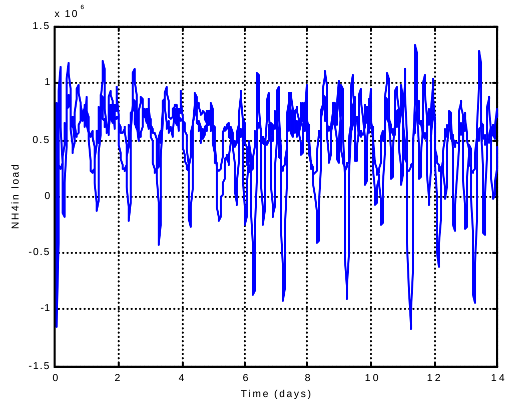


***Figure 3c :*** *Plant results using DAC #1 : Estimation of the NH4in load*

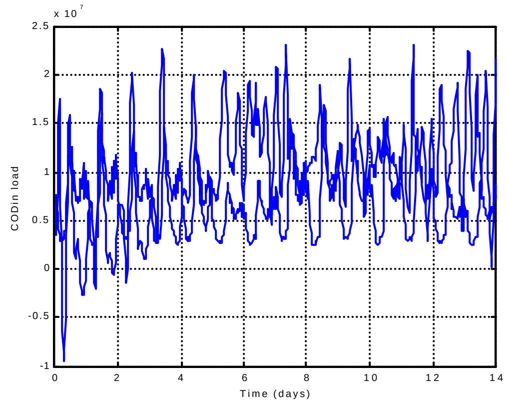


***Figure 3d :*** *Plant results using DAC #1 : Estimation of the CODin load*

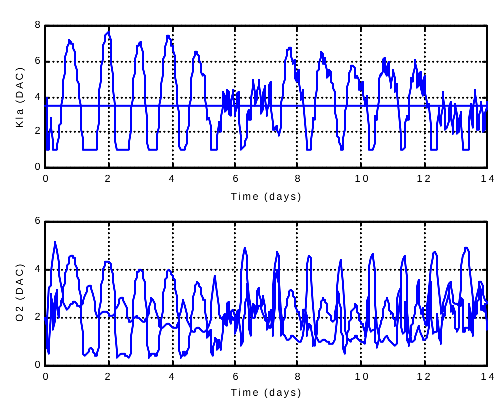


***Figure 4a :*** *Plant results using DAC #2 : $Kl_a$ / $O_2$*

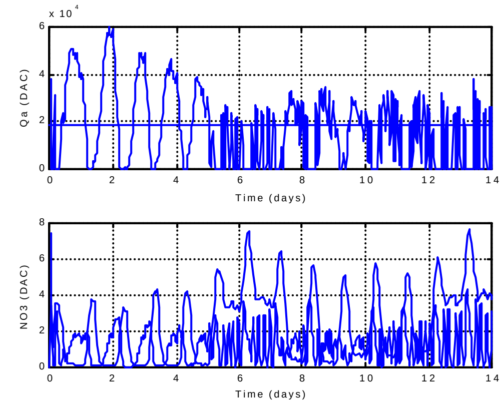


***Figure 4b :*** *Plant results using DAC #2 : $Q_a$ / $NO_3$*

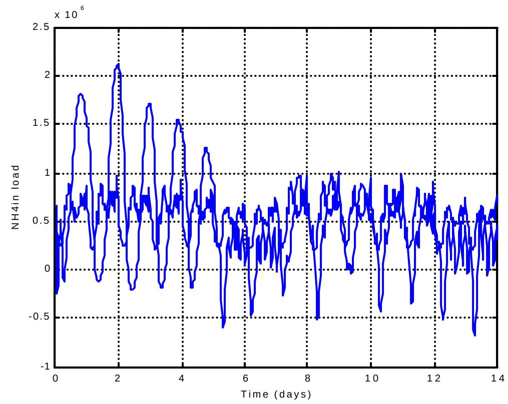


***Figure 4c :*** *Plant results using DAC #2 : Estimation of the NH4in load*

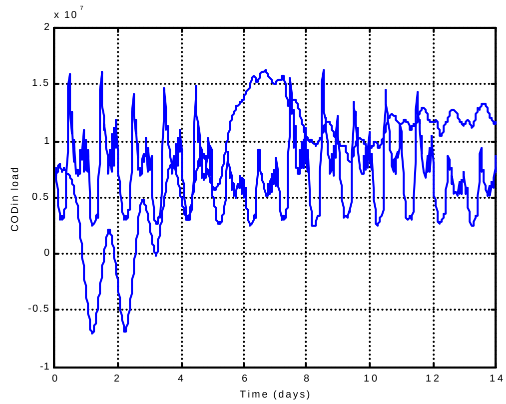


***Figure 4d :*** *Plant results using DAC #2 : Estimation of the CODin load*

## 5.- DISCUSSION

Although the identified state space model was quite good, the regulation results of the implementation of the DAC were not completely satisfactory when compared to those obtained with the two decentralized PI controllers. It can be explained by two different reasons. First, it is to be noticed that the tuning of a DAC controller is a very difficult task. In particular, the computation of the optimal values of the weighting matrices *Q* and *R* is very delicate and has not been optimized for the study. Second, remember that the dynamics of the oxygen and of the nitrate are very different. For example, notice that the proportional PI gain for the DO controller was 2.448 while equal to 9785 for the internal recirculation controller. As a consequence, it is even more difficult to tune the centralized DAC controller. However, it is to be noticed that the input estimator exhibited some excellent results as shown in Figure 3c and 3d. From this point of view, an additional point can be stated : when good regulation results are obtained with the DAC strategy, then the estimation of the input NH4 and COD loads are bad (*Cf.* Figures 4). Conversely, when relatively bad regulation results are obtained (as those presented in Figures 3), then estimation results are better. These two extreme cases reported here come from the fact that a DAC is an observer-based regulator. Then, there exists an optimal trade-off between the rate of convergence of the estimator and the dynamic of the controller.

With respect to the additional information it is able to provide for diagnosis purposes (estimation of the input loads in several pollutants), the use of the DAC is obviously very interesting. As noticed above, from a regulation point-of-view, the decentralized strategy gives better performances than the centralized one due to the large difference between the dynamics of the two considered feedback loops. Last but not least, notice that the estimator (based on the Disturbance Modeling Principle and synthesized using a Kalman filter) can be used independently of the associated feedback. Thus, in fact, it appears that the two strategies should be used simultaneously and independently : the two decentralized PIs controllers for regulation purposes and the second strategy for estimating the unmeasured disturbance inputs. Moreover, notice that these estimates can be used as well within the PI strategy in adding a feedforward term.

## 6.- CONCLUSIONS AND PERSPECTIVES

In this paper, the comparison between two control strategies for the optimization of an ASP benchmark model was realized. From a regulation point-of-view, it was noticed that the industrial decentralized strategy gives better results than the centralized one due to a very large difference in the dynamics of the variables to be controlled. The simultaneous use of the two strategies (the first one for control purposes and the second one for diagnosis purposes) was suggested. The use of the estimates obtained using the Disturbances Modeling Principle for being used within a PI feedback/feedforward strategy is now being investigated.

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