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CONTROL LAWS BASED ON SOFTWARE SENSORS FOR OPTIMISING THE PERFORMANCE OF SBRs

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Abstract: This report describes the proposed control solutions for the problem of increasing the performance of WWTPs. For the Carbon removal case (Eoli Model 1, EM1) an Event Driven Time Optimal Control (EDTOC) is proposed. It exhibits characteristics that are desirable in a practical solution: requires little knowledge of the mathematical model and parameters of the plant, uses only sensors of proven technology, rejects the dangerous inlet toxicant concentration perturbations and reduces significantly the treating time and, consequently, the energy consumption. For the carbon and nitrogen removal case (Eoli Model 2, EM2), a sub optimal control strategies is proposed. This control is a model based approach and it requires a mathematical model and advanced sensors. Its objective is to reduce the total reaction time. This control takes into account the variations of the influent concentrations and proposes a sequence of aerobic and anoxic phases.

Keywords: Activated sludge WWTP, Sequencing Batch Reactor (SBR), Optimal Robust Control, Software Sensor

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1. Introduction

In this project, three types of wastewater are considered. The first one coming from a dairy industry, contaminated with organic carbon components as well as nitrogen, the second typical for an area including chemical industry, containing toxic or recalcitrant compounds, the third one a domestic wastewater which occasionally contains toxic or organic overloads. They are grouped in two model classes: one with only Carbon as the substrate to be removed (denoted EM1: EOLI Model 1), and another with Nitrogen, where nitrification and denitrification are needed (denoted EM2).

The control laws proposed in this WP are therefore linked to the specific application in accordance with its model. Chapter two presents the Control Law devoted to EM1 that deals with the toxic wastewater treated by UNAM and IBTech; while chapter three is dedicated to EM2, related to the WWTP for the following partners: UU, LBE and POLIMI (+ENEA as subcontractor).

2. Control Law for EM1 process (wastewater at UNAM and IBTech)

2.1. *EM1 dynamical model*

The main process is related to the first reaction describing the degradation of the treated toxic substrate via aerobic digestion. The originally proposed model was:

$$4Cl \cdot Phenol + O_2 \rightarrow X_1 + CO_2 + (metabolite) \qquad \text{reaction (A)}$$

$$(O_2 + metabolite \rightarrow X_2 + CO_2) \qquad \text{reaction (B)}$$

with X_1 and X_2 the corresponding biomasses for both reactions, respectively.

Experimental results showed that the metabolite is only produced if there is strong inhibition; otherwise there is only a weak quantity of metabolite. Moreover, it is not directly measurable. For this reason, and considering that no strong inhibition should occur if optimal control laws are applied, it was decided to avoid useless problem complexification and to simplify the model considering only the one main reaction (A), which indeed represents the most relevant and important behaviour, for control purposes, of the EM1 type WWTP.

The main idea for controlling the reaction phase is to use a fed-batch approach, manipulating the inlet flow rate F_{in} in the SBR, to optimise (i.e. to reduce) the treatment time. So a process model considering the fill and react phases (settling, decanting and idling phases

are not addressed here) was needed. It was developed in WP2 as EM1. Let us denote S_C, S_O, and X respectively, the concentration of the substrate to be treated (i.e. 4-Chlorophenol) *(also denoted simply as S in some related publications)*, the concentration of the dissolved oxygen (DO) in the water *(also denoted simply as O)* and the concentration of the biomass for the first reaction.

$$S_C + S_O \xrightarrow{} X + CO_2 \qquad \text{reaction (A) simplified}$$

Using the simplified version of reaction (A), a simple mass balance leads us to obtain the following EM1 equations for the Standard Operation conditions of the SBR (fill and react phases only, acclimated, not strongly inhibited, no Oxygen limitation, bounded inflow):

$$\frac{dX}{dt} = \left(\mu - \frac{F_{in}}{V}\right)X \tag{1}$$

$$\frac{dS_C}{dt} = -k_1\mu X + \frac{F_{in}}{V}\left(S_{C,in} - S_C\right) \tag{2}$$

$$\frac{dV}{dt} = F_{in} \tag{3}$$

$$\frac{dS_O}{dt} = -(k_2\mu + b)X + \frac{F_{in}}{V}\left(S_{O,in} - S_O\right) + K_L a\left(S_{O,sat} - S_O\right) \tag{4}$$

where k_1, k_2, b, K_La, $S_{C,in}$, $S_{O,in}$, $S_{O,sat}$ and V are the yield coefficient for substrate degradation *(also denoted as $1/Y_{x/s}$ or simply $1/Y$)*, the oxygen yield coefficient *(also denoted as $1/Y_{x/o}$)*, the specific endogenous respiration rate of the biomass in the water *(also denoted as r)*, the oxygen mass transfer coefficient, the influent substrate concentration *(also denoted as S_{in} or simply S_i)*, the influent DO concentration *(also denoted as or O_{in} simply O_i)*, the saturation DO concentration in the liquid medium *(also denoted as O_{sat} or simply O_s)* and the wastewater volume being treated in the SBR tank, respectively.

As the substrate (i.e. 4-Chlorophenol) inhibits the biomass growth, the Haldane model can be applied to approximately describe the specific growth rate of the biomass, μ, such as:

$$\mu = \frac{\mu_{\max} S_C}{K_S + S_C + \frac{S_C^{\,2}}{K_I}} \tag{5}$$

where $\mu_{\max}$, K_S and K_I are the maximum specific biomass growth rate *(also denoted as μ_o)*, the Michaelis-Menten affinity constant and the inhibition constant for a Haldane kinetics model of the specific biomass growth rate, respectively.

Remark 1- Inhibitory model structure:
The Haldane model is just a reference. Any inhibitory model with a similar structure, i.e. exhibiting a single unique maximum μ^* at $S_C=S_C^*$ and tending to zero as S_C tends to either infinity or zero, as in Fig.1, should also be accounted for. Note that if S_C^* is allowed to go to infinity the model structure changes and inhibition is no longer present. The same is true if $S=S_C^*$ is not reachable.

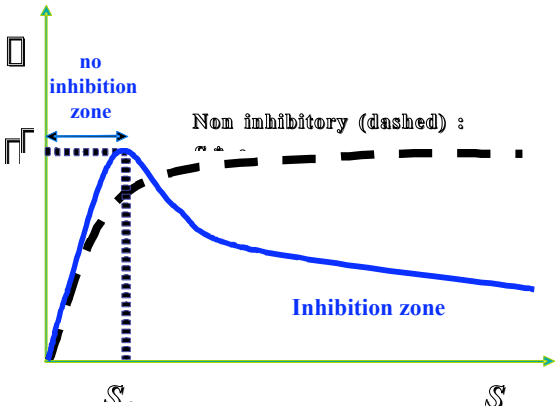

Figure 1. Two different specific biomass growth rate models: The continuous line represents $\mu(S_C)$ for an inhibitory substrate (it grows monotonically until reaching a unique maximum μ^* @ $S_C=S_C^*$ and then decreases, also monotonically). The dashed line depicts the non inhibitory case.

2.2. *EM1 control challenge*

The problem formulation states that, for technical and economical reasons, neither toxicant nor biomass concentrations are measurable on-line. Additionally, parameter $S_{C,in}$ is highly uncertain and even time-varying. It is therefore to be considered unknown and unmmeasurable, so it becomes the main perturbation for the carbon removal process. A nominal $S_{C,in}$ value is assumed for designing the SBR and for acclimation of the biomass, but such a value is only a statistical reference and should not be considered for individual batch operations. If an arbitrary open-loop uncontrolled F_{in} was to be used (i.e. batch mode) then high values for such a parameter may inhibit the SBR and, moreover, peak shock load values, i.e. unexpected and unknown extremely high toxicant substrate concentrations in the inflow, may even disable it permanently. The experimental work done for developing EM1 also shows that model parameters as k_1, k_2, b, $S_{O,in}$, μ_{max}, K_S and K_I are uncertain too, while K_La, $S_{O,sat}$ are easy to identify with certitude.

The challenge for designing a control that increases the SBR performance is then to use only the available measurements (Dissolved Oxygen, S_O, and Volume level, V) to achieve minimum treating time, while rejecting the main unmmeasurable perturbation $S_{C,in}$, relying only in the more certain parameters (K_La, $S_{O,sat}$) or, at least, being robust against uncertainties of all other parameters that might be needed for control purposes. The control must also perform in such a way that the EM1 standard operation conditions are preserved, that is that no strong inhibition do happen ever and that no deacclimation (i.e. because strong starvation) occurs. Bounds in inflow rate and in reaction time must also be considered. This means that no infinite (nor negative) inlet flow rate values are allowed and that convergence time (if any) for software-sensors and for controllers should be negligible compared to the total reaction time of a single batch.

Remark 2- Bounds:
There are natural conditions for the problem that impose restrictions to EM1 in equations (1-5). All variables and parameters should be strictly positive and bounded, as should also be the total treating time for any single batch, i.e. the time horizon for the solution is finite.

Remark 3- Actuator and Sensors:
Although handling dilution $D=F_{in}/V$ as a control variable may be theoretically easier, for practical reasons (constant flow rate pumps are cheaper and more robust than variable ones) we choose to manipulate directly the inflow rate, i.e.

bounds for real actuators must be considered in the problem formulation explicitly, i.e. $0 = F_{min} \leq F_{in} \leq F_{max}$. Moreover, as real sensors are prone to get saturated and to exhibit delays and/or high frequency non modeled behaviors, the standard operating condition of the SBR must be designed in such a way as to avoid these problems, i.e. the choice of F_{max} should consider both sensor related delays, which makes it desirable to use a low value, and maximum allowable total filling time.

Assumption 1- Perturbation:

Influent substrate concentration may vary largely and even, in very rare cases, be almost inexistent (no toxicant in the feed). However to simplify the problem, without sacrificing generality, a natural condition is assumed: the influent's toxicant concentration is greater than the singular one ($S_{C,in} > S_C^*$), furthermore it must always be greater than the one inside the SBR to the point that, if the influent pump is turned on to its maximum value, then the toxic concentration inside the tank will always increase, i.e. $F_{in} = F_{max} \_ dS_C/dt > 0$

2.3. *Event Driven Time Optimal Control (EDTOC)*

A Time Optimal Control (TOC) for the SBR guarantees that the problems posed in previous section 2.2 are addressed. But a direct approach to implement such a TOC may require knowing, with certitude, the value of most of the model parameters and also the measurement of the unmmeasurable variables. The original plan for solving the challenge included the use of the measurable variables, fed to a Software-Sensor, in order to estimate the value of the unmmeasurable variables and/or parameters needed for controlling the plant, specifically substrate concentrations (in the influent and inside the tank). While working on such an idea a different, but related, approach was discovered. In fact, it was learned that for controlling the reaction in an optimal way it is not really necessary to know, at all, the substrate concentrations but, instead, it suffices to know the relation of the value of the reaction rate to its maximum reachable value. Exploiting such an idea did lead to the development of the Event Driven Time Optimal Control (EDTOC) which is a practical, realisable, bang-bang approximation of the TOC.

The EDTOC will be explained in the next subsections: first a description of the optimal law will be made, then an approximation to that law by means of a bang-bang (on/off) control will be given and, finally, a way to drive such a bang-bang approach by using only the available measurements will conclude the explanation.

2.3.1 **Time Optimal Control (TOC)**

The optimal feeding profile for a minimum time fed-batch operation of the SBR is well known for EM1 type processes (Moreno, 1999). The advantage of applying such an optimal profile is that most of the main problems associated with the standard Fixed Time Control (FTC) batch-mode operation of the SBR could be solved, i.e. the substrate concentration inside the SBR is kept near the maximum possible value that does not cause inhibition, S_C^*, thus preventing inhibition. Moreover, the instant at which the reaction ends could be perfectly known, thus allowing to avoid both starvation and premature decantation of the SBR. The difficult thing to do is to practically implement a control law that behaves in such an optimal theoretical way.

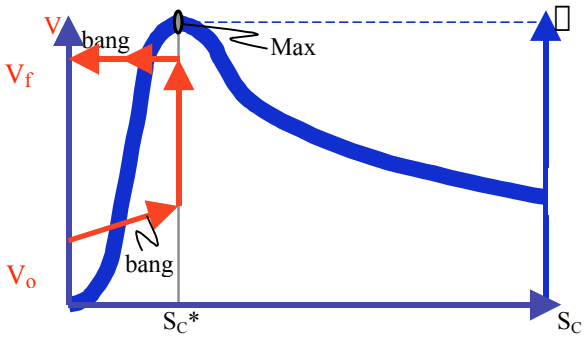

Figure 2. Optimal trajectory, projected into the S_CV plane, composed of 3 arcs (arrows). Note that the singular arc is vertical, meaning the SBR is filled without altering the internal toxicant concentration S_C. The secondary axis shows, superimposed, □(S_C)

The TOC trajectory path consists of three arcs as shown in Fig. 2. The feeding profile to obtain it consists, respectively, of three segments. The first one starts when the filling phase starts at $V=V_o$ and is a bang-bang one, meaning the actuator is set to one of its limit values in order to allow the system's trajectory to go, as fast as possible, to a point where $S_C=S_C$*. Typically the initial substrate concentration lies in the left region of S_C* so the actuator gets set to its maximum value F_{max}. Once $S_C=S_C$* the second, singular, segment begins. The inflow is changed to a singular one (F_{sng} at Eq.6; Moreno, 1999) that maintains $S_C=S_C$* at all times just until the reactor gets full i.e. $V=V_f$. The last step is also a bang-bang one, to turn off the inlet flow, i.e. $F_{in}=0$, and wait until the toxicant inside the reactor gets below some acceptable $S_{C,f}$ maximum finishing limit. After that the final settling and drawing phases in the SBR sequence may be initiated.

$$F_{sng} = \frac{k_1 \square^* VX}{S_{C,in} \square S_C^*} \tag{6}$$

2.3.2 **EDTOC: a bang-bang realization to approximate the Time Optimal Control**

If S_C could be measured and □ could be completely known then a simple way to implement an approximation to the TOC would be to use feed-back in a bang-bang law, as depicted in Figures 3 and 4. Two switching limits are needed (Fig.3), one low (S_l) to turn on the inlet pump, as long as the tank is not yet full, when $S_C<S_l$ and other high (S_h) to turn it off. As this solution depends on logical events to drive the Bang-Bang switching it will be called Event Driven Time Optimal Control (EDTOC)

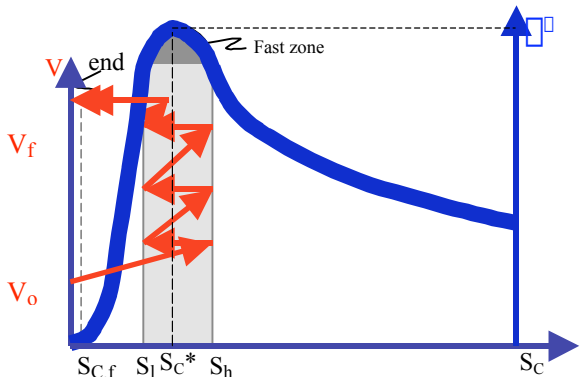

Figure 3. Bang-Bang trajectory for the EDTOC, projected into the S_CV plane. The secondary axis superimposes □ in order to relate it to the switching limits (S_l, S_h) for S_C. The initial and final Volume level of the SBR tank in any single batch are denoted as V_o and V_f respectively.

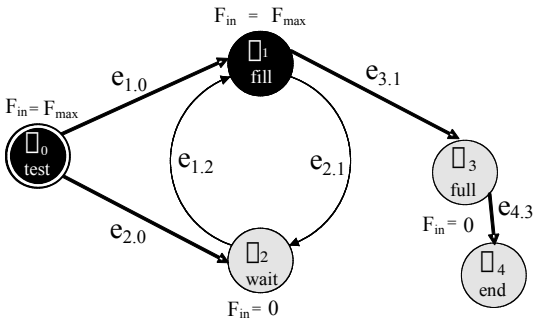

Figure 4. Finite states automata representation of the bang-bang approximation to the EDTOC. The initial state q_0 performs a test to asses the initial condition of the process in terms of toxicant substrate. An occurrence of an event $e_{k,j}$ (see Table 1) drives the system from a given state q_j to a new one q_k. Note: if the current state is other than q_j then any event $e_{k,j}$ has no effect in the system status.

Table 1. Events driving the bang-bang approximation to TOC

Tag	Event	Meaning
$e_{1.0}$	$S_C \leq S_C^*$	Not Inhibited
$e_{2.0}$	$S_C > S_C^*$	Inhibited
$e_{2.1}$	$S_C \geq S_h$	MustWait (stop filling)
$e_{1.2}$	$S_C \leq S_l$	MustFill (fill at maximum flow rate)
$e_{3.0}$; $e_{3.1}$	$V \geq V_{max}$	TankFull
$e_{4.3}$	$S_C \leq S_{C,f}$	EndReaction

Note that the initial and final arcs of the TOC solution are perfectly followed by such an EDTOC approximation when the standard conditions are fulfilled. If that is not the case and the initial conditions depart from the standard one in such a way that $S_{C,0}$ happens to be greater than S_C^* (i.e. the systems starts inhibited) then the test state q_0 will put the system in the right path by jumping to q_2 instead of q_1 (see Fig.4). The singular arc (vertical arrow in Fig.2) is approximated by using a sequence of Bang-Bang arcs, i.e. the zig-zaging arrows in Figure 3 produced by the alternative cycling of q_1 and q_2 in Figure 4. Note also that this approximation may be done as fine as desired by choosing $S_{l,h} \_ S_C^*$, *i.e.* the EDTOC solution is suboptimal but may be done as close to the optimal as desired. Furthermore it is robust against influent concentration perturbations ($S_{C,in}$ value is not involved in the solution).

The problem is that, not having a way to measure S_C, the events in Table 1, needed to drive the bang-bang switching of the influent pump, are not available. Next subsection will show how to detect such events, indirectly, without measuring S_C and without exactly knowing the exact formula for φ.

2.3.3 **Events Software-Sensor for the EDTOC**

Next the explanation about how to use a function φ of φ (Fig. 5) to estimate the events needed to operate the Bang-Bang solution previously explained will follow. A physical meaning and the way to compute such a φ function will be given in the next subsection so, for now, let us assume φ is measurable (see Fig. 6) and focus on the Software-Sensor workings.

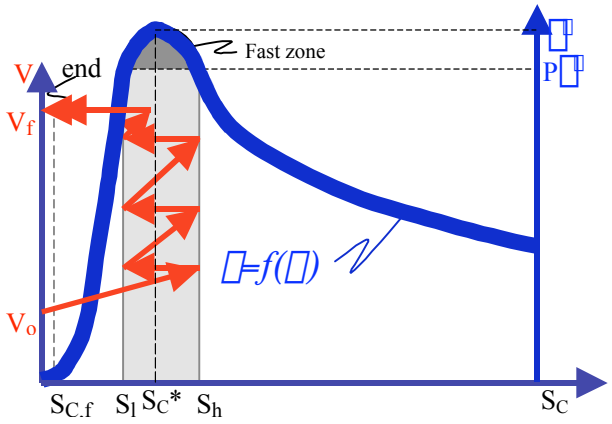

Figure 5. Bang-Bang trajectory for the EDTOC projected into the S_CV plane. The secondary axis superimposes a function of that keeps its shape even if some features remain unknown. 0<P<1 is a tuning parameter; the closer it gets to "1" the closer to the optimal is the solution.

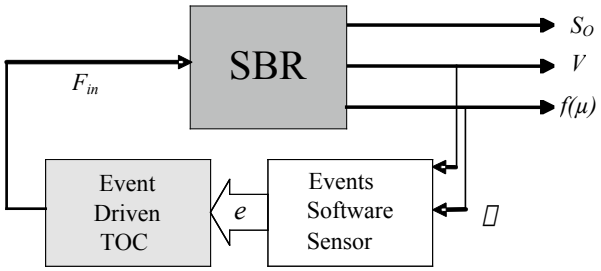

Figure 6. Event Driven Time Optimal Control scheme, assuming a measurable does exists.

There are various ways to estimate the events described in Table 2 for the control architecture given in Figure 6. The classical one would be to use a regular observer to estimate S_C and, independently, get to know S_l and S_h. After that a simple comparison allows to generate the events that depend on them. In such a solution the observer uses the measurable variables to estimate a continuous analog variable (i.e. substrate concentration S_C, as in Vargas *et al.*, 2000) which is later used to compute a logical one (i.e. the event ***e*** itself). By contrast the new solution we propose estimates directly the logical event ***e***, without caring for the actual real value of S_C and/or S_l, S_h. Avoiding the intermediate step of estimating S_C makes the solution easier to implement, more robust and independent of most of the, otherwise needed, model parameters.

It will be assumed that $f(\mu)$, in Figures 5 and 6, is a strictly monotonic increasing and continuous function of μ, as for example Equation 7, for *a, b, c* unknown constants, $a, c>0$. The maximum $\_^*=\max_{Sc\geq 0} f(\mu(S_C))=f(\mu^*)$ is then well defined. It should be noted that it is not necessary to know the exact shape of μ or $f(\mu)$. If Assumption 1 is satisfied, and because the monotone increasing (decreasing) behavior of $S_C(t)$ when it goes from S_l to S_h (from S_h to S_l, respectively), it is clear that (t) increases from $\__l = f(\mu(S_l))$ ($\__h = f(\mu(S_h))$) until maximum $\_^*$ and then decreases until $\__h$ ($\__l$ respectively). If $\_^*$ is assumed constant but unknown, this leads to the scheme in Figure 6. There, the Events Software-Sensor (ESS) estimates a maximum of $f(\mu)$ in real time, as $_k^*(t)=\max(f(\mu(S_C(\))))$ for $\ (t_k,t)$, were t_k is the instant when the last k^{th} state change in the EDTOC took place.

$$\Omega = f(\mu) = (a\mu + b)c \quad (7)$$

Comparing the actual values of Ω and Ω_k* allows to determine if $S_C=S_l$ or $S_C=S_h$ have been reached, even if S_C, S_l and S_h do remain unknown. In particular, consider $S_l<S$* and $S_h>S$* such that $f(\mu(S_l))=f(\mu(S_h)) = P\_$*, where $0<P<1$ is a near-optimality control parameter. Making P close to one renders S_l, S_h close to S*. Figure 5 shows the relation between S_l, S_h, _* and P for the case $\Omega = f(\mu) = (a\mu+b)c$. The ESS also determines easily if $S_C>S$* or not, i.e. if the system is in the inhibition zone (see Table 2).

Table 2. Estimation of the Events for driving the bang-bang approximation to theTOC

Tag	Event trigger	Estimates	Meaning
$e_{1.0}$	$d\Omega/dt>0$	$S_C \cong S_C$*	Not Inhibited
$e_{2.0}$	$d\Omega/dt<0$	$S_C > S_C$*	Inhibited
$e_{2.1}$	$\Omega \cong P\Omega_k$	$S_C \geq S_h$	MustWait (stop filling)
$e_{1.2}$	$\Omega \cong P\Omega_k$	$S_C \cong S_l$	MustFill (fill at maximum flow rate)
$e_{3.0}$; $e_{3.1}$	$V \geq V_{max}$	(measured)	TankFull
$e_{4.3}$	$\Omega < \Omega_f$	$S_C \cong S_{C,f}$	EndReaction

Table 2 shows the events estimated by the ESS. Using such events the EDTOC shuts down or powers up the influent pump F_{in} as appropriate. The finite state EDTOC is exactly the same as depicted earlier in Figure 4. The initial state at $k=0$ for $t=t_0=0$ is always Ω_0. If inhibited, the system will jump instantaneously to state Ω_2. After the initial bang-bang arc, the cycling between Ω_1 and Ω_2 will approximate the singular arc. Once the tank is filled, Ω_3 will complete the last bang-bang arc. The reaction finishes when Ω_4 is reached. After this the rest of the batch sequence (settling, draw…) may be completed and, afterwards, a whole new batch cycle may be started.

2.3.4 **Practical Events Software-Sensor (ESS)**

In the previous subsection a Ω variable, used to estimate the events driving the EDTOC, was assumed to be measurable, but that is not the case. In this subsection a Ω candidate is analyzed: the total Oxygen Mass consumed by the total biomass per Time unit. It is estimable (i.e. computable using signals coming from sensors of proven mature technology as Dissolved Oxygen concentration and Volume level) and it does have a clear physically meaning.

In usual terms Ω [MT^{-1}] is chosen to be equivalent to *Volume* [L^3] times the *Oxygen Uptake Rate* (OUR) [$MT^{-1}L^{-3}$]. Note that because of the stoichiometric relation between them, for a given Biomass value, maximizing such Oxygen Mass Uptake Rate (OMUR) is equivalent to maximizing the Substrate degradation rate, which is just another way to look at the optimality objective for the problem at hand. And that is what the EDTOC does, to maximize Ω. In this subsection it will be shown how the ESS itself may real-time compute such a Ω=OMUR, using only the available variables F_{in}, S_O and V, to generate the events needed for control, as depicted in Figure 7.

The Dissolved Oxygen Concentration in the liquid medium of the SBR changes depending on the difference between the Oxygen Transfer Rate (OTR), the Biomass Oxygen Uptake Rate (OUR) and the dilution effect as shown in Eq. 8 (Bastain and Dochain, 1990)

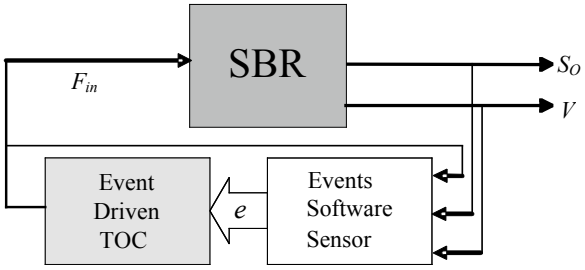

Figure 7. Event Driven Time Optimal Control scheme for the given available variables

$$\frac{dS_O}{dt} = OTR - OUR - \frac{F_{in}S_O}{V} \tag{8}$$

Comparing Equations 4 and 8 it is easy to see that the OUR depends on both the oxygen consumption due to the exogenous respiration and the one owed to the metabolic activity of the Biomass, as expressed in Equation 9. If both sides are multiplied by V Eq.10 is obtained, where $B=XV$ is the total biomass mass and Ω is the Oxygen Mass Uptake Rate (OMUR).

$$OUR = (k_2\Omega + b)X \tag{9}$$

$$OMUR = V \cdot OUR = (k_2\Omega + b)B \tag{10}$$

Note the similarity between Equations 7 and 10. If just B was constant then OMUR in Equation 10 could be used as the Ω in Equation 7, for the ESS in the EDTOC. And that is almost just the case for the EM1 toxicant removal process. Experiments performed by WP1 show that the total biomass ($B=XV$) increase during a single standard batch reaction for EM1 is less than 2%. i.e. from a practical point of view it is almost constant. Moreover, if fed-batch EDTOC is used instead of FTC (pure batch mode) then various fill-wait sub-cycles will be performed during a single reaction, and the increase of B during each individual sub-cycle is even less. For example if 4 sub-cycles are performed during a single batch then the change of B during each one of them (on or off) semi-cycles is around 0.25% (Remember that the total biomass growth follows a stoichiometric relation, so it depends on the total mass of substrate treated and not on the time spent to do it). A full analysis for the case when B cannot be assumed to be almost constant is given in Betancur *et al*. (2005).

Now, to compute such a Ω note that from Equations 4 and 7, and considering the usual case in which the influent is deprived from oxygen ($S_{O,in}$=0), Eq.11 follows, which depends only on available variables and parameters, *i.e.* it is real-time computable.

$$\Omega = OMUR = F_{in}S_O + K_l a\,(S_{O,sat} - S_O)V - V\frac{dS_O}{dt} \tag{11}$$

As long as close to the standard conditions are preserved for EM1 the EDTOC could be applied directly to the real SBR as explained above. However, if effects such as non-modeled sensor dynamics become important then EDTOC performance may get degraded. That could be the case if F_{max} is badly chosen (too high) or if $S_{C,in}$ is extremely high (extreme shock loads), or if tuning parameter P is chosen too close to 1 (heavy actuator switching rate), as in all of these cases the time needed for the system to go from $S_C=S_l$ to $S_C=S_h$ would be too short for the Dissolved Oxygen Sensor to follow the real S_O dynamics, and hence the OMUR will be computed badly. Practical aspects as considering the time delay introduced by sensors, and the option of using variable flow rate pumps to adapt the inflow in order to increase practical robustness against very high shock loads, are considered in Betancur *et al.* (2004)

3. Control Law for EM2 type process

3.1. *EM2 dynamical model*

The Model used to derive the control law is adapted from the EM2b developed in the Deliverable D2.3. The original model assumes that carbon and nitrogen removal are realized in two steps : aerobic and then anoxic phases. The model is therefore based on the following reaction scheme :

1: Anoxic phase

(Reaction A)

(Reaction B)

2: Aerobic phase

(Reaction C)

(Reaction D)

(Reaction E)

Experimental results showed that the dynamic of the ammonification reactions B and E is fast compared to the other reactions. Moreover, it is considered that in aerobic phase oxygen (S_O) is not limiting due to a high oxygen transfer rate applied for the LBE reactor. In order to consider only biodegradable substrate and to simplify the model representation we introduce the following notations :

, , and

Following the above assumptions, the original model is simplified and only the following reactions are considered :

1: Anoxic phase

(Reaction A_{bis})

2: Aerobic phase

(Reaction C_{bis})

(Reaction D_{bis})

The model parameters are adjusted and re-identified for this new structure as it is described in [Mazouni et al 2005]. Furthermore, a control variable is introduced to represent the switching signal between aerobic and anoxic phase: for the aerobic mode and for the anoxic mode. The new model is then written as :

(8)

(9)

(10)

(11)

(12)

The main objective of the control is to reduce the substrate concentrations up to normative limits while reducing to total time. i.e minimal time control with a specified target. With this purpose the variation of the biomass concentrations are free and in order to reduce

the complexity of the problem the model is reduced as follow using the mass balance conservation principle arising in batch processes :

From equations (8), (9), (11), and (12), we can easily derive the following :

(13)

(14)

and by integration we get :

(15)

(16)

where m_1 and m_2 depend only on the initial conditions and remain constant during a batch operation whatever the control is. It is a consequence of the mass conservation principle which states that the quantities of x and S_{NH} that disappear are transformed into biomass. Thus one obtains a linear relation between x and X_h (resp z and X_a):

(17)

(18)

One can replace expressions of X_h and X_a given by (17) and (18) to obtain the reduced order model :

(19)

(20)

(21)

where — and —

3.2. *EM2b control approach*

Nitrogen removal in batch reactor for wastewater treatment is commonly realized in two successive steps : denitrification and nitrification. Usually, the reactors are a priori designed for a known range of concentrations. The reactor volume and the phase durations are fixed. However, if there are significant variations of the influent concentrations, no guarantee on the effluent purification is given and the possibility of carrying out both reactions in the batch is not assured. In this kind of process, the reactions are related and the final concentrations have to reach a terminal target.

The purpose of the control is to drive the state of the process from an initial point to a target C_N defined by equations (22) to (24) in minimal time by switching between anoxic and aerobic modes. As the biomass concentrations are free, the third order reduced model (equations (19) to (21)) is used to derive the optimal control law.

(22)

(23)

(24)

To handle the problem we process as follows :

1. Geometric tools are used to study the dynamic behavior of the third order model in order to characterize the admissible solutions i.e. how can the process reach the final target?
2. When the possible solutions are defined, numerical optimization is used to find the optimal solution.

3.2.5 **Admissible solution**

A controllability analysis was performed. The main result shows that the state space is composed of two parts :

1. a reachable set : where admissible solutions exist. In this case, at most one anoxic phase is sufficient to reach the target.
2. an unreachable set $^{3+}$ (C_N) where no admissible solution is possible.

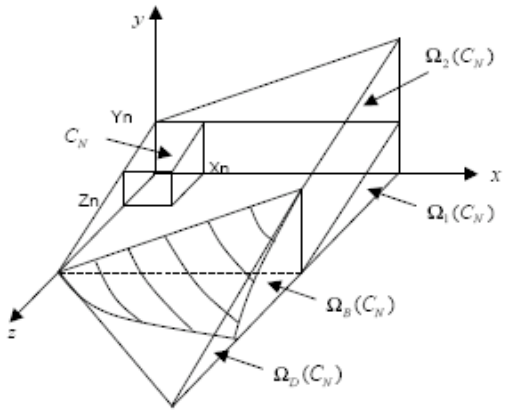

Figure 8 reachable set:

This result is obtained using a mathematical model. In practice, some restrictions need to be considered.

1. The process is represented by two models (an aerobic model and an anoxic model) where the operator can switch from one to another. In practice, biological process commutation is quite slow and the models can not be valid at high switching frequency.
2. If we consider the ratio *x/z*, the case studied in the EOLI project corresponds to the major cases in practice. The nitrogen removal reaction is very slow compared to the carbon removal. The aerobic time corresponds essentially to the nitrogen removal time. Since this last one is not eliminated in anoxic phase, the aerobic phase is time constant. We can reduce the total cycle time by reducing the anoxic phase time.

For these reasons, we considered only solutions with at most one anoxic phase. In this case the set of admissible controls is given by: aerobic, anoxic, aerobic-anoxic, anoxic-aerobic and aerobic-anoxic-aerobic. In order to find the sub-optimal solution for this problem we consider the general solution given by:

(25)

where .

To cover all the possible solutions one or more of the three intervals can be empty.

3.2.6 **Sub optimal solution**

In this section, we consider only trajectories with initial conditions in the reachable set. The optimal problem is converted into a sub-optimal problem where switching instants t_1 and t_2 need to be determined to minimize the total reaction time as it is illustrated in figure 9

(26)

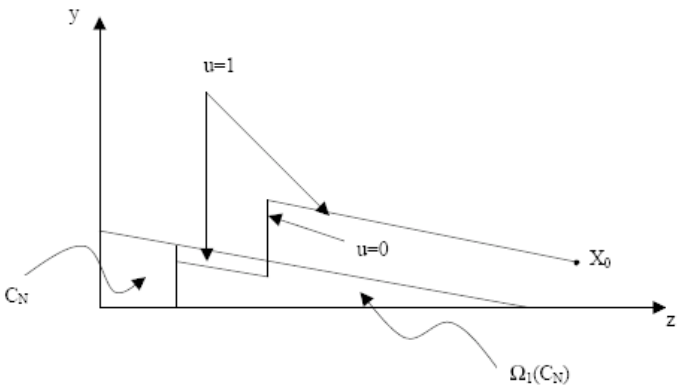

Figure 9 : Projection of the general solution on the YZ plan

The determination of these parameters follows an algorithm first proposed in [Mazouni et al 2005]. The main results are:

If : . Only one aerobic phase is applied until reaches the target

If :

- is given when one of the quantities J_1 or J_2 (defined below) reaches its minimal. In the case where J_1 and J_2 are only increasing the batch starts with anoxic phase i.e
- is given when reaches . In the case where reaches the target the batch finishes with an anoxic phase (i.e.) and the final state corresponds to :
- is given when reaches the target. Two cases are possible

or

where :

, (Cf, figure 9)

and —

3.2.7 **Numerical optimization**

To optimise the total cycle time, one needs only to compute (using a numerical optimisation) and that minimize respectively the quantities and . Two trajectories are then generated where their corresponding solutions verify respectively the boundary conditions : and . It is a question here of comparing both of the solutions and to choose the optimal one. It is possible that one of the two solutions is not feasible. In this case, and as we choose only initial conditions in the reachable set, the second one should be feasible and is automatically chosen.

3.2.8 **Interpretation of the supobtimal solution**

The nitrogen removal kinetics is very slow compared to the carbon removal. Thus, the required aerobic time corresponds essentially to the nitrogen removal. Since nitrogen is not eliminated in anoxic phase, the aerobic phase duration cannot be minimized. We can only reduce the total cycle time by reducing the anoxic phase time.

In standard cases the anoxic phase takes place at the beginning of the cycle. The anoxic reaction rate depends on the two substrate concentrations S_C and S_{NO} (respectively x and y). At the beginning, the maximum of carbon is available. The suboptimal control strategy consists in starting with an aerobic phase to maximise the anoxic reaction rate. During the first aerobic phase, S_{NO} increases and S_C decreases (in this case the anoxic rate can increase and then decrease or only decrease). The anoxic phase is applied when the maximal possible rate of the anoxic reaction is reached, so that the total time of this phase is reduced. Of course if the maximum anoxic rate is obtained at the initial time, the batch starts with the anoxic phase as in the classical standard case : in such a case, this solution is the optimal one and the total time cannot be further reduced.

3.3. *Practical implantation*

The prospect idea for the on line implantation of the this control is to estimate J_1 and J_2 using on-line sensors and software observers. For the moment, a practical solution cannot be considered because this method needs advanced sensors with high frequency measurements for at least two of the three substrates S_C , S_{NH} and $S_{NO.}$ The technical obstacle is that, with the actual available on-line sensors, only one or two samples can be realized during the first aerobic phase and no more during the anoxic phase. In other words, under the actual functioning conditions, it means that the gain it is possible to obtain using this advanced strategy is less than the maximum measurement sample time it is possible to obtain with available advanced instrumentation. However, the theoretical study pointed out the possibility of a new strategy, that is adding an aerobic phase at the beginning of the treatment cycle.

Furthermore, it is possible – under the condition that a sufficiently accurate model is available – to apply the optimal strategy in open loop. Indeed, an off-line application can be realized where the switching instants are computed before starting the batch using a mathematical model. In addition, during the batch process, this trajectory is "checked" on-line using, for instance the hardware sensors developed within the workpackage WP3 even if their associated sampling periods are quite large. Two measurement points per phase can be considered to be sufficient to check the first and the last point of each phase.

Conclusions

The proposed Event Driven Time Optimal Control (EDTOC) solves all of the problems stated for EM1 type processes. It demands little knowledge of the mathematical model and parameters of the plant, is easy and economic to implement, and allows to increase significantly the performance of the WWTP.

For the EM2b, a model-based optimal control algorithm was developed to reduce the total reaction time for carbon and nitrogen removal. The direct application needs advanced sensors and online measurements for both influent and effluent wastewater. The practical solution proposed is the off line application where the optimal trajectories are generated using the model and then the calculated switching times are applied to the real plant.

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