Adaptive Fuzzy Control of the Dissolved Oxygen Concentration in an Activated Sludge Process

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Abstract

In this paper an adaptive fuzzy control strategy for dissolved oxygen concentration (DO) control of an activated sludge process is proposed and evaluated in a benchmark simulation model. The controller uses DO concentration error feedback and manipulates the flow control valves supplying air to the bioreactor cells. The results of simulation shows that this adaptive controller can optimize control rules resulting in an accurate controls of dissolved oxygen.

1 Introduction

Wastewater treatment plants (WWTPs) are large non-linear systems subject to large perturbations in influent flow rate and pollutant load, together with uncertainties concerning the composition of the incoming wastewater. Nevertheless these plants have to be operated continuously to a level that natural systems can safely absorb their effluent, requiring facilities of increasing scale and sophistication.

Most treatment facilities use some type of activated sludge process in which naturally occurring microorganisms are cultivated in the wastewater under conditions that optimize the consumption of influent biodegradable organic matter [2]. Control issues in Activated Sludge (AS) processes pertain primarily to DO control through aeration, taking into account energy usage optimization and satisfying process demands, i.e., the provision of adequate oxygen without excessive aeration and its associated energy cost, despite changing influent conditions. The variations of the input flow concentrations and flow rate suggest an on-line tuning of the controller parameters, in order to proper react to the input disturbances and operation points.

Several approaches that attempt to control the ASP process have been reported in the literature. These range from Fuzzy, Model Based Predictive control, and a number of advanced multi-variable techniques. See for example [1, 4, 8, 9, 11, 15].

What is analyzed in this paper is the suitability of applying a design methodology for adaptive fuzzy control of dissolved oxygen (DO) concentration. The method was designed and tested on a benchmark simulation model of an AS process.

Generally, the basic objective of adaptive control is to maintain consistent performance of a system in the presence of uncertainties or unknown variations in plant parameters and structures. The most important advantage of adaptive fuzzy control over conventional adaptive control is that adaptive fuzzy controllers are capable of incorporating linguistic fuzzy information from human operators, whereas conventional adaptive controllers are not.

Fuzzy control is desirable from a practical point of view because it is easy to understand. Fuzzy control permits the emulation of human control strategies. Thus, the underlying principle can be easily understood by those who are not control specialists. Also, fuzzy control is reasonably simple to implement.

The implementation presented here therefore is the regulation of the DO level to a user-specified set point in an AS reactor within a wastewater treatment plant. The aim is to maintain the DO level regardless of the influent disturbances. The paper is organized as follows. Section 2 presents a description of the process as well as operating considerations. Section 3 explain why and how the DO control is taken in consideration. Section 4 shows the mathematical background of the the adaptive fuzzy controller, and explain how it is constructed and implemented in the DO control problem. Section 5 presents the simulation results. Finally, Section 6 makes concluding remarks.

2 Benchmark simulation model

Development and performance evaluation of innovative control strategies should be based on a rigorous methodology including a simulation model, plant layout, performance criteria and test procedures. Hence, the Benchmark Simulation Model n.1 (BSM1) [6] is considered in this paper. It is a platform-independent simulation
environment defining a plant layout, a process model, influent data, test procedures and evaluation criteria.

2.1 Plant Layout and Process Model

The BSM1 is composed of five biological reactors in series with a secondary settling tank. Fig. 1 shows a schematic representation of the layout. The total biological volume is 5999 m$^3$ (1000 m$^3$ for tanks 1 and 2, 1333 m$^3$ for tanks 3–5). Tanks 1 and 2 are un aerated but fully mixed when tanks 3–5 are aerated using a maximum oxygen transfer coefficient ($K_L a$) of 240 d$^{-1}$ and a dissolved oxygen saturation of 8 g O$_2$ m$^{-3}$. The plant is designed for an average influent dry-weather flow rate of 18.446 m$^3$ d$^{-1}$ and an average biodegradable chemical oxygen demand (COD) in the influent of 300 g m$^{-3}$.

The AS Model n.1 [3] has been selected to describe the biological phenomena taking place in the biological reactors shown in Fig 1. The model is highly mechanistic, where the major components of relevance and the most important biological processes have been identified, and it is based on a COD balance of the system (oxygen is expressed as negative COD). The secondary settler is a non-reactive unit (i.e. no biological reaction) with a total volume of 6000 m$^3$ (area of 1500 m$^2$ and depth of 4 m) subdivided into ten layers and taking into account the vertical transfers between layers. The 6th layer (counting from bottom to top) is the feed layer. The settling model used is a double exponential settling velocity function proposed by [10].

The layout presents two internal recycles: the nitrate internal recycle from the fifth to the first tank at a default flow rate of 55.338 m$^3$ d$^{-1}$ and the sludge recycle from the underflow of the secondary settler to the front end of the plant at a default flow rate of 18.446 m$^3$ d$^{-1}$ (as there is no biological reaction in the settler, the DO concentration in the recycle is the same as in the fifth tank reactor).

2.2 Influent Disturbances

The disturbances used to test a particular control strategy play a critical evaluation role. Because of the multifaceted nature of activated sludge, a particular control strategy may react well to a disturbance and not well to another. Thus, to carry out a complete and unbiased evaluation, it is necessary to define a series of disturbances and to subject each control strategy to all the disturbances. Three influent disturbances, representative of different weather conditions, have been defined on BSM1: dry weather, rain weather (a combination of dry weather and a long rain period) and storm weather (a combination of dry weather with two storm events). Each scenario contains 28 days of influent data with intervals of 15 min. The benchmark is then evaluated for the last 7 days of dynamic data.

3 Dissolved Oxygen Control

Aeration is a crucial part of the whole activated sludge process, because aerobic conditions are conducive to the growth of a wide variety of microbes, including heterotrophic bacteria, which consume biochemical oxygen demand from the wastewater, as well as nitrifying bacteria, which oxidize ammonia to nitrate. Because of the aeration energy cost (which can represent up to 50% of the total plant costs) and the strong effect of aeration on biomass growth, dissolved oxygen (DO) concentration control is the most studied control problem in wastewater treatment [2].

3.1 Dynamics of the Dissolved Oxygen

The oxygen mass balancing is modeled by the following equation [7]:

$$\frac{dS_{O,k}}{dt} = \frac{Q_{k-1} S_{O,k-1} - Q_k S_{O,k}}{V_k} - r_{S_{O,k}} + (S_{O,sat} - S_{O,k})(K_L a)_k$$

where, on aerated reactor $k$, we have: $V_k$ is the reactor volume; $Q_k$ is the reactor flow rate; $Q_{k-1}$ is the reactor inflow rate; $S_{O,k-1}$ is the DO concentration entering the reactor; $S_{O,k}$ is the DO concentration in the reactor; $(K_L a)_k$ is the oxygen transfer coefficient; $S_{O,sat}$ is the saturation concentration for oxygen; and $r_{S_{O,k}}$ is the rate of use of DO by biomass. Because the BSM1 not consider the hydraulic dynamic of the plant, and the reactors are connected in cascade, it is assumed that $Q_k = Q_{k-1}$.

As shown in [3], there are another 12 nonlinear differential equations in the ASM1 model needed to determine $r_{S_{O,k}}$, requiring knowledge of the control input $(K_L a)_k$, flow rate $Q_k$, and sophisticated information concerning the parameters of the wastewater inflow into the zone. This means that the complete state-space model of the DO concentration is described by nonlinear dynamics of a very high order.

3.2 Dissolved Oxygen Control Architecture

In order to maintain the DO concentration at a given level, an adaptive fuzzy control architecture is employed. It is assumed that the DO concentration is measured by an ideal sensor in the reactor. The DO concentration value is controller by the adaptive fuzzy control, which generates the control command $K_{L,a}$ that is applied to the reactor in order to maintain the oxygen concentration level. Fig.2 depicts the control architecture. The $(K_{L,a})_k$ describes the oxygen transfer process from an aerator to the activated sludge and it is, in general, nonlinear and depends on the
aeration actuating system and sludge conditions, however, for reasons of simplicity is considered to be ideal with regard to their behavior.

From (1) the disturbance cited in section 2.2 has an impact on \( S_{O,k} \) through \( Q_k, S_{O,k-1} \) and \( r_{S_{O,k}} \). In this work, the control problem is under heavy uncertainty because only DO sensors are available and all the disturbance are taken as unknown. Thus, an adaptive control methodology is a good solution to tackle the problem.

4 Adaptive Fuzzy Controller

An adaptive fuzzy controller is constructed from a set of fuzzy IF-THEN rules whose parameters are adjusted on-line according to some adaptation law for the purpose of controlling the plant to track a given trajectory. In this paper, an adaptive fuzzy controller is designed based on the Lyapunov synthesis approach.

Roughly speaking, adaptive fuzzy controllers may be designed through the following steps: first, construct an initial controller based on linguistic descriptions (in the form of fuzzy IF-THEN rules) about the unknown plant from human experts; then, develop an adaptation law to adjust the parameters of the fuzzy controller on-line.

4.1 Description of Fuzzy Systems

The basic configuration of the fuzzy logic system considered in this paper is shown in Fig. 3. The fuzzy system performs a mapping from \( U \subset \mathbb{R}^n \) to \( \mathbb{R} \). We assume that \( U = U_1 \times \cdots \times U_n \), where \( U_i \subset \mathbb{R}, i = 1, 2, \cdots, n \). The fuzzy rule base consists of a collection of fuzzy IF-THEN rules [12]:

\[
R^i : \text{IF } x_1 \text{ is } F^i_1 \text{ and } \cdots \text{ and } x_n \text{ is } F^i_n \text{ THEN } y \text{ is } G^i
\]  

(2)

where \( x = (x_1, \ldots, x_n)^T \in U \) and \( y \in \mathbb{R} \) are the input and output of the fuzzy system, respectively, \( F^i_1 \) and \( G^i \) are labels of fuzzy sets defined in \( U_i \) and \( \mathbb{R} \), respectively, and \( i = 1, 2, \ldots, M \).

The fuzzy inference engine performs a mapping from fuzzy sets in \( U \) to fuzzy sets in \( \mathbb{R} \), based upon the fuzzy IF-THEN rules in the fuzzy rule base and the compositional rule of inference. The fuzzifier maps a crisp point \( x = (x_1, \ldots, x_n)^T \in U \) into a fuzzy set in \( U \). On the other hand, the defuzzifier maps fuzzy sets in \( \mathbb{R} \) to a crisp point in \( \mathbb{R} \). Further details can be found in [12].

The fuzzy logic systems of Fig. 3 comprise a very rich class of static systems mapping from \( U \subset \mathbb{R}^n \) into \( \mathbb{R} \), because within each block there are many different choices, and many combinations of these choices can result in useful subclasses of fuzzy logic systems. Now it will be consider one subclass of fuzzy systems which will be used as building block of the adaptive fuzzy controller used in this work.

The set of fuzzy systems with singleton fuzzifier, center-average defuzzifier, and product inference engine can represent functions \( f : U \subset \mathbb{R}^n \to \mathbb{R} \) of the form:

\[
y(x) = \frac{\sum_{i=1}^{M} \bar{y}^i \left( \prod_{i=1}^{n} \mu_{F^i_i}(x_i) \right)}{\sum_{i=1}^{M} \left( \prod_{i=1}^{n} \mu_{F^i_i}(x_i) \right)}
\]

(3)

where \( x = (x_1, \ldots, x_n)^T \in U, \bar{y}^i \) is the point at which \( \mu_{G^i} \) achieves its maximum value (without loss of generality, we assume that \( \mu_{G^i}(\bar{y}^i) = 1 \)), and \( F^i_1 \) and \( G^i \) are fuzzy sets in (2).

If the antecedent membership functions \( \mu_{F^i_i}(x_i) \) are fixed, and \( \bar{y}^i \) is considered adjustable parameters, then (3) can be written as

\[
y(x) = \theta^T \bar{\xi}(x)
\]

(4)

where \( \theta = (\bar{y}^1, \ldots, \bar{y}^M)^T \in \mathbb{R}^M \) is a parameter vector, and \( \bar{\xi}(x) = [\xi^1(x), \ldots, \xi^M(x)]^T \) is a regressive vector with the regressor \( \xi^i(x) \) (called fuzzy basis function in [14]), defined as

\[
\xi^i(x) = \frac{\prod_{i=1}^{n} \mu_{F^i_i}(x_i)}{\sum_{i=1}^{M} \left( \prod_{i=1}^{n} \mu_{F^i_i}(x_i) \right)}.
\]

(5)

4.2 Problem Statement

Consider the nth-order nonlinear systems of the form:

\[
x^{(n)} = f \left( x, \dot{x}, \cdots, x^{(n-1)} \right) + bu,
\]

\[
y = x
\]

(6)

where \( f \) is unknown continuous function, \( u \in \mathbb{R} \) and \( y \in \mathbb{R} \) are the input and output of the system, respectively,
and  \( x = (x_1, x_2, \cdots, x_n)^T = (x, \dot{x}, \cdots, x^{(n-1)})^T \in \mathbb{R}^n \) is the state vector which is assumed to be available from measurements. In the spirit of the nonlinear control literature [5], these systems are in normal form and have the relative degree equal to \( n \).

To design the controller, it has to be determined a feedback control  \( u = u(x(\theta)) \) based on fuzzy systems (4) and an adaptive law for adjusting the parameter vector \( \theta \) such that the tracking error,  \( e \equiv y_m - y \), should be as small as possible, i.e., the plant output \( y(t) \) should follow the ideal output \( y_m(t) \).

### 4.3 Adaptive fuzzy control approach

Let  \( e = (e, \dot{e}, \cdots, e^{(n-1)})^T \) and  \( k = (k_n, \cdots, k_1)^T \in \mathbb{R}^n \) be such that all roots of the polynomial  \( h(s) = s^n + k_1 s^{n-1} + \cdots + k_n \) are in the open left-half plane. If functions \( f \) is known, then the control law

\[
u^* = \frac{1}{b}[-f(x) + y_m^{(n)} + k^T e].
\]  
(7)

Substituting (7) in (6) results in

\[
 e^{(n)} + k_1 e^{(n-1)} + \cdots + k_n e = 0,
\]  
(8)

which implies that  \( \lim_{t \to \infty} e(t) = 0 \). Since \( f \) is unknown, the optimal control,  \( u^* \), cannot be implemented. The goal is to design a fuzzy logic control  \( u_c(x(\theta)) \), in the form of (3), to approximate this optimal control. Substituting  \( u_c \) in (6) and after some straightforward manipulation, the closed-loop dynamics of the fuzzy control system becomes

\[
e^{(n)} = -k^T e + b [u^* - u_c(x(\theta))].
\]  
(9)

Let

\[
\begin{bmatrix}
0 & 1 & 0 & 0 & \cdots & 0 & 0 \\
0 & 0 & 1 & 0 & \cdots & 0 & 0 \\
0 & 0 & 0 & 1 & \cdots & 0 & 0 \\
0 & 0 & 0 & 0 & \cdots & 1 & 0 \\
-k_n & -k_{n-1} & \cdots & \cdots & \cdots & \cdots & -k_1 \\
0 & 0 & \cdots & \cdots & \cdots & \cdots & 0 \\
0 & 0 & \cdots & \cdots & \cdots & \cdots & 0
\end{bmatrix}
\]

\[
b_c = [0 \quad 0 \quad \cdots \quad 0 \quad b]^T,
\]  
(10)

then the dynamic equation (9) can be rewritten into the vector form

\[
\dot{e} = \Lambda_c e + b_c [u^* - u_c(x(\theta))].
\]  
(11)

Let the optimal parameter vector is

\[
\theta^* = \arg\min_{\theta \in \mathbb{R}^{n'}} \left[ \sup_{x \in \mathbb{R}^n} |u_c(x(\theta)) - u^*| \right]
\]  
(12)

and the minimum approximation error is

\[
\omega \equiv u_c(x(\theta^*)) - u^*.
\]  
(13)

Using (13), the error equation (11) can be rewritten as

\[
\dot{e} = \Lambda_c e + b_c \phi^T \xi(x) - b_c \omega
\]  
(14)

where  \( \phi \equiv (\theta - \theta^*) \), and  \( \xi(x) \) is a fuzzy basis function in the form of (5).

The task of the adaptation law is to determine an adjusting mechanism for  \( \theta \in \mathbb{R}^{n'} \) such that the tracking error  \( e \) and the parameter error  \( \phi \) is minimized. To complete this task, consider the Lyapunov function candidate

\[
V = \frac{1}{2} e^T Pe + \frac{1}{2\gamma} \phi^T \phi
\]  
(15)

where  \( \gamma \) is a positive constants, and  \( P \) is a positive definite matrix satisfying the Lyapunov equation

\[
\Lambda_c^T P + PA_c = -Q
\]  
(16)

where  \( Q \) is an arbitrary \( n \times n \) positive definite matrix, and  \( \Lambda_c \) is given by (10). The time derivative of  \( V \) along the trajectory of (14) is

\[
\dot{V} = -\frac{1}{2} e^T Q e - e^T Pb_c \omega + \frac{1}{2\gamma} \phi^T \left[ \gamma e^T Pb_c \xi(x) - \dot{\theta} \right].
\]  
(17)

In order to minimize the tracking error  \( e \) and the parameter error  \( \phi \),  \( \dot{V} \) should be negative. Since fuzzy systems (3) or (4) are universal approximators, then it can be expected that  \( \omega \) should be small. Besides that, since  \(-\frac{1}{2} e^T Q e \) is negative, a good strategy is to choose the adaptation law such that the last two terms in (17) are zero, that is, the chosen adaptation law is

\[
\dot{\theta} = \gamma e^T Pb_c \xi(x).
\]  
(18)

Finally, the linguistic information is specified and then can be directly incorporated into the adaptive fuzzy controller assuming that there are the following linguistic descriptions about the unknown function  \( u_c \):

\[
R^{(r)} : IF x_1 \text{ is } A_{1r}^c \text{ and } \cdots \text{ and } x_n \text{ is } A_{nr}^c \text{ THEN } u_c \text{ is } B^r
\]  
(19)

where  \( A_{ir}^c \) and  \( B^r \) are labels of fuzzy sets in  \( \mathbb{R} \), \( r = 1, 2, \cdots, L \). The case  \( L = 0 \) is admissible and means that there are no linguistic control rules. Therefore, linguistic information in the form of (19) is not necessary and are here for the purpose of emphasizing that this adaptive fuzzy controller can directly incorporate these fuzzy control rules (if there are any) into its design. However, good linguistic information can helps to construct a good initial controller allowing a faster adaptation.

### 4.4 Design Steps of Dissolved Oxygen Control

The adaptive fuzzy controller of Sec. 4 will now be applied to control the dissolved oxygen system whose dynamics are characterized by (1). The primary goal of the
control is to maintain the dissolved oxygen concentration at a given level in the last compartment. Thus, the objective is to design a fuzzy logic control $u_c(x, \theta)$, which are designed in the form of (3) or (4). This is accomplished by the following steps for the design of the adaptive fuzzy controller:

First of all, let $e = e = S_{O,\text{ref}} - S_O$, and $U_c \in [-1, 1]$. Now, the design of the adaptive fuzzy controller is accomplished by the following steps [13]:

step 1 Chose vector $k = [1]$ so that all roots of the polynomial $h(s) = s + k_1$ are in the open left-half plane, and an arbitrary positive definite matrix $Q = [10]$ in order to solve Lyapunov equation (16) to obtain a positive definite matrix $P = [5]$. 

step 2 Define fuzzy sets $F^j_i$, where $j = 1, \ldots, 5$, whose membership functions $\mu_{F^j_i}$ uniformly covering $U_c$ as follows:

$$
\mu_{F^1_1}(x) = \frac{1}{1 + \exp^{0.5(x, +21.5)}}, \\
\mu_{F^2_1}(x) = \exp^{-(x, 0 + 0.35)^2}, \\
\mu_{F^3_1}(x) = \exp^{-(x, - 0)^2}, \\
\mu_{F^4_1}(x) = \exp^{-(x, 0 - 0.35)^2}, \\
\mu_{F^5_1}(x) = \frac{1}{1 + \exp^{0.5(x, -21.5)}}.
$$

step 3 Construct the fuzzy rule base for the fuzzy system $u_c(x, \theta)$ whose IF parts comprise all the possible combinations of the $F^j_i$. The fuzzy rule base was designed as follows:

$$
R^i : \text{IF } x \text{ is } F^j_i \text{ THEN } u_c(x, \theta) = \tilde{g}^j_i, \tag{20}
$$

where $x = e$. Assuming that there are no predefined linguistic rules designed by human knowledge, choose $\tilde{g}^j_i = 0, \forall i \in \{1, 2, \cdots, 5\}$.

step 4 Construct the fuzzy basis function $\xi^j(x)$ based on (5). Collect the centers of the consequent fuzzy sets $\tilde{g}^j_i$ into the initial condition vectors $\theta_0(x)$. Note that $u_c(x, \theta)$ is constructed as

$$
u_c(x, \theta) = \theta^T \xi(x). \tag{21}
$$

step 5 Apply the feedback control (21) to the plant.

step 6 Chose an arbitrary $b = 100 > 0$ and $\gamma = 4 > 0$ and use the adaptation law given by (18) to calculate the new vector $\theta$, and return to step 5. Note that this free parameters of the controller is tuned by trial-and-error method.

5 Simulations and Results

The efficiency of the adaptive fuzzy control algorithm is validated by comparison with the PI control described originally in the benchmark. In this paper, data of the last seven days of a 28-day dry weather dynamic simulation are considered, preceding days are used for stabilization of the system. The same DO sensor defined within the benchmark were applied. Dissolved oxygen sensors are the most commonly used in practice for on-line control or monitoring. Since the dissolved oxygen sensors are proven to be robust and reliable with relatively fast response times, the benchmark dissolved oxygen sensors are assumed to be ideal with no delay and noise.

5.1 Performance Assessment

The objective of the adaptive fuzzy controller is to provide robust control in a wide range of process operation points. Thus, the primary goal of the control is to maintain the dissolved oxygen concentration at a given level in the last compartment. It was used three DO set-points: 1, 2 and 3 mg/l. For the sake of comparison of the different control strategies, their performance is assessed by the integral of absolute error ($IAE$), integral of square error ($ISE$), maximal deviation form set-point ($MAD_e$) and maximum absolute variation of control signal in one sample ($MADV_{dK,\alpha}$). The obtained values of the performance assessment are given in Table 1. It has to be noted,

Table 1: Comparative performance of the dissolved oxygen controllers

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<thead>
<tr>
<th>$S_{O,\text{ref}} = 1$</th>
<th>$S_{O,\text{ref}} = 2$</th>
<th>$S_{O,\text{ref}} = 3$</th>
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<tr>
<td>$IAE$</td>
<td>$ISE$</td>
<td>$MAD_e$</td>
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<tr>
<td>Fuzzy</td>
<td>0.0166</td>
<td>9.91 e-05</td>
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<tr>
<td>PI</td>
<td>0.1422</td>
<td>0.0071</td>
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<tbody>
<tr>
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<td>2.98 e-04</td>
</tr>
<tr>
<td>PI</td>
<td>0.2977</td>
<td>0.0306</td>
</tr>
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</table>

that internal recycle flow control was also applied in the benchmark besides the DO control, however, for the sake of direct evaluation only DO control has been applied in this simulation, recycle flow rate is kept constant in both cases.

Figs. 4 and 5 shows the comparison of dissolved oxygen concentration and control effort in the third aerated reactor with $S_{O,\text{ref}} = 1$, respectively.

The performance of the Adaptive Fuzzy Controller is mostly affected by the parameter $\gamma$, because it influences
Figure 4: Comparison of the dissolved oxygen concentration in the third aerated reactor with $\text{S}_\text{O,ref} = 1$ (solid line: adaptive fuzzy control; dashed line: PI control).

Figure 5: Comparison of control effort in the third aerated reactor with $\text{S}_\text{O,ref} = 1$ (solid line: adaptive fuzzy control; dashed line: PI control).

Figure 6: Comparison of impact of $\gamma$ on the attenuation of disturbance on dissolved oxygen concentration (blue line: $\gamma = 1$; red line: $\gamma = 2$; cyan line: $\gamma = 3$; black line: $\gamma = 4$).

the pace of the adaptation and the velocity of reaction to the unknown disturbances. Fig. 6 shows the simulation results for four different values of $\gamma$.

Through these results, the adaptive fuzzy controller presented great robustness with respect to unknown disturbances when applied to the control of dissolved oxygen concentration in a wastewater treatment plant simulator, especially when compared with PI controller described originally in the benchmark.

It should be kept in mind that the results presented are based on a simulation model, which is only an approximation of the real process. Therefore, full-scale experiments would also be needed in order to additionally support the results. However, despite the strong mathematical background, the adaptive fuzzy controller is simple to implement in practice. Because fuzzy control emulates human control strategy, the underlying principle can be easily understood by those who are not control specialists. Besides that, even if the available knowledge of plant is not very accurate, the adaptive characteristics of the controller presented in this work can make use of the fuzzy information in a systematic and efficient manner.

6 Conclusion

This work has considered the regulation of the dissolved oxygen concentration to a user-specified set-point. The suitability of applying a design methodology for adaptive fuzzy control was investigated and tested on a benchmark simulation model of an activated sludge process. This adaptive fuzzy control has two major qualities: 1) does not require an accurate mathematical model of the system under control, 2) is capable of incorporating fuzzy control rules directly into the controllers, but does not depend on prior knowledge of plant.

Very promising results have been obtained after the investigation of the properties and tracking performance of the controller when compared with PI controller described originally in the benchmark. These enhancements includes integral of absolute error and integral of square error much smaller when compared with PI control, and better response to disturbances.

Acknowledgement

This work was supported by the Fundação para a Ciência e a Tecnologia (FCT), and ISA - Intelligent Sensing Anywhere, under Bolsa de Doutoramento em Empresa Fellowship SFRH/BDE/33295/2008.

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