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Supervisory control system to enhance partial nitrification in an activated sludge reactor

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ABSTRACT

This work proposes a supervisory control system based on an optimization layer to calculate the optimum pH and dissolved oxygen (DO) set-points for the SISO controller, maintaining the process at stable partial nitrification. Takagi–Sugeno fuzzy multimodels were implemented to estimate ammonium degradation and nitrite accumulation from on-line DO and pH values, and updated using off-line measurements. An activated sludge reactor was operated successfully over 115 consecutive days with the supervisory control system, achieving ammonium degradation and nitrite accumulation values higher than 95% and 80%, respectively. The on-line estimates of the multimodels showed a prediction error of less than 7% at steady state operation, and reflected the tendencies shown in experiment to be caused by changes in pH value and DO concentration.

1. Introduction

The biological nitrification–denitrification process makes it possible to remove high nitrogen loads from industrial effluents generated by, e.g. the fishing, chemical and food processing industries. During the nitrification process, ammonia-oxidizing bacteria (AOB) oxidate ammonium (NH_4^+) to nitrite (NO_2^-), and subsequently, nitrite-oxidizing bacteria (NOB) oxidate nitrite to nitrate (NO_3^-). The nitrate is then sequentially reduced by heterotrophic denitrifying bacteria (step 1, Fig. 1) to molecular nitrogen (N_2) as the final product. As the nitrite is consumed during nitrification and built up again during denitrification, the oxidation of nitrite (nitratation) becomes an unnecessary step [1], since it is feasible to denitrify the nitrite directly to molecular nitrogen, as shown in Fig. 1 (step 2). Partial nitrification to nitrite (step 2) has three practical advantages: 25% lower oxygen consumption, 40–60% lower need of organics for denitrification, and lower sludge production [1].

In order to achieve partial nitrification, attempts have been made to inhibit or limit nitratation (NOB) (step 1, Fig. 1) by applying low concentrations of oxygen (<2 mg O_2/L) and high pH values (>8) [2]. It has been found, however, that the nitrifying bacteria somehow become acclimatized to these conditions [3], and nitrite accumulation is reduced in the long term. The hypothesis is therefore proposed that the establishment of unfavourable environmental conditions for NOB bacteria may avoid acclimatization and maintain inhibition on a long term-basis. Using a process control approach, this study proposes the development of a supervisory system which uses an optimization layer to set pH and DO values in order to establish environmental conditions favourable to AOB growth and unfavourable to NOB growth [4–6].

Supervisory systems have been developed to improve the performance and increase the operational reliability of the plants. Supervisory control systems include process monitoring, fault diagnosis, process optimization, set-point generation for SISO control, and decision support [7].

Some supervisory control strategies in large-scale plants require on-line ammonium, nitrite and nitrate measurements [8], which involves major investment. To confront this problem, authors such as Tomiello et al. [8], Pirsing et al. [9], and Jianlong and Ning [10], have made use of two types of experimental measurements: on-line, e.g. DO, pH and temperature measurements; and off-line, e.g. daily analyses of substrate concentrations. This approach has also been adopted in industrial-scale facilities [8].

Rodríguez-Roda et al. [12] propose a three level structure for a supervisory control system in an activated sludge process. There is a lower layer for data gathering, including on-line data acquisition, SISO control, and off-line data obtained from laboratory analysis. The intermediate layer consists of an expert system and a case-based reasoning system for the diagnosis and detection of

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Nomenclature

AOB	ammonia-oxidizing bacteria
AIC1	controller device to regulate pH by manipulating the addition of carbonate
AIC2	controller device to regulate the dissolved oxygen in the reactor by manipulating the airflow injected
$c_{NH_4^+}$	inlet ammonium concentration in the reactor (mg N/L)
$c_{NH_4^+,R}$	ammonium concentration in the reactor (mg N/L)
$c_{NO_2^-,R}$	nitrite concentration in the reactor (mg N/L)
$c_{NO_3^-,R}$	nitrate concentration in the reactor (mg N/L)
DO	dissolved oxygen (mg/L)
DO*	AIC2 controller set-point (mg/L)
$G(s)$	transfer function
NOB	nitrite-oxidizing bacteria
pH*	AIC1 controller set-point
Q_c	carbonate inflow to the reactor, variable manipulated by AIC1 controller
Q_a	airflow supplied to the reactor, variable manipulated by AIC2 controller
T	reactor temperature (°C)

Greek letters

α	ammonium oxidation index
$\hat{\alpha}$	estimated ammonium oxidation index, local estimation of the multimodel
β	nitrite accumulation index
$\hat{\beta}$	estimated nitrite accumulation index, local estimation of the multimodel

anomalous situations. At the highest level, mathematical models are used to predict and search for optimum operating conditions.

A decision support level can be constructed based on expert systems [8,11,13–16]. Pires et al. [14] propose a fuzzy control system based on manipulated variables, such as the external recycle and by-pass flow rates, to ensure low concentrations of nitrate, nitrite and COD in the plant effluent. Tomiello et al. [8] use fuzzy rules of the Takagi–Sugeno type to determine the set-points of SISO controllers for oxygen and biomass concentration, in order to maintain a high COD range and total nitrogen conversion. Serralta et al. [17] incorporate a supervisory control using knowledge-based systems [18] and activated sludge models like the ASM1 [19] to modify the DO set-point when a change in the inlet concentration of ammonium occurs. Rodríguez-Roda et al. [12] also report a supervisory system using the ASM1 model to search for optimum operating conditions. Because the structure of these white box models is very complex, the number of scenarios evaluated is limited.

The use of an optimization layer at decision support level has been reported, principally in batch processes [20–22]. Coelho et al. [20], Kim et al. [21] and Chachaut et al. [22] manage to reduce aeration time and total batch time in a Sequencing Batch Reactor by means of non-linear optimization. Instead of white box models, we propose to use fuzzy logic such as Takagi–Sugeno multimodels [23]. These models make it possible to use heuristic algorithms to search for optimum operating conditions [24] and help to establish simpler supervisory control systems in plants with well-known behaviour. In an effort to innovate in the development of the decision support level, this study proposes the following objectives:

- to implement Takagi–Sugeno fuzzy models capable of estimating ammonium degradation and nitrite accumulation from on-line DO and pH measurements;
- to implement a self-tuning technique to set parameters from experimental data, enabling the models to adapt to new operating scenarios;
- to develop a supervisory system using heuristic optimization to search for DO and pH set-points, leading to efficient operation of the nitrification process (high α and β indices).

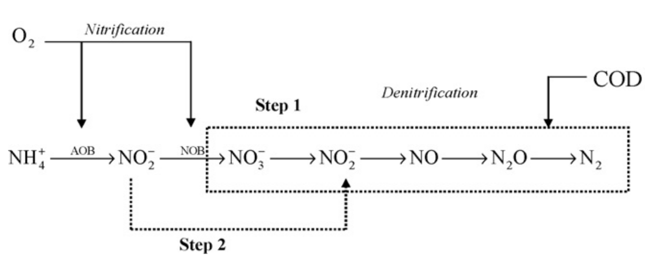


Fig. 1. Integrated nitrogen removal. Step 1: classical nitrification–denitrification and step 2: short-cut via nitrite accumulation.

In Section 2 we present the instrumentation of the activated sludge reactor, the SISO control, the proposed fuzzy multimodels and the optimization method. In Section 3 we present the predictions of the Takagi–Sugeno fuzzy models and the operation of the activated sludge nitrification reactor using the supervisory control system.

2. Materials and methods

Partial nitrification was evaluated on the basis of nitrite accumulation (β) and ammonium oxidation (α). Nitrite accumulation corresponds to the fraction of total ammonia nitrogen oxidised to nitrite, as a function of total oxidation to nitrite and nitrate. Thus the efficiency indices α and β were calculated as follows:

$$\beta = \frac{c_{NO_2^-,R}}{c_{NH_4^+,R} + c_{NO_3^-,R}}, \quad 0 \le \beta \le 1 \tag{1}$$

$$\alpha = \frac{c_{NH_4^+,O} - c_{NH_4^+,R}}{c_{NH_4^+,O}}, \quad 0 \le \alpha \le 1 \tag{2}$$

2.1. Reactor and instrumentation

The nitrification process was carried out in a laboratory-scale activated sludge system, consisting of a 2 L reactor with a 1 L settler. The plant schema and its instrumentation are presented in Fig. 2. The reactor was kept homogenized by a mechanical stirrer (HEIDOLPH, RSR 2050, Germany) at 360 rpm. The temperature (T) was controlled by means of a thermostat (Julabo, Model EC, Germany). The on-line measurement and transmission of T/pH and dissolved oxygen (DO) were effected by two electrodes (HACH, EC 310, USA, and WTW, Oxi 701, Germany, respectively). The pH was controlled by the addition of Na_2CO_3 0.2 M using a diaphragm pump (LANG, type ELADOS EMP II, 41 L/h, Germany). Aeration was supplied by an aquarium aerator (COSMOS double type 1000, China) and effected by using pulse width modulation (PWM) for pneumatic valve opening (Festo, 457, MSG-24DC, Germany). Furthermore, the system was automated by the use of a PLC (Siemens, Simatic S7-200, CPU 214), operated with a PC/PLC interface programmed in MATLAB® 6.5. The T, pH, consumption of Na_2CO_3 solution, and DO concentration were measured and recorded on-line approximately every second by the KepServer data acquisition program [25]. Communication between MATLAB ® (client) and the KepServer (server) was effected by using DDE (Dynamic Data Exchange Protocol, Microsoft).

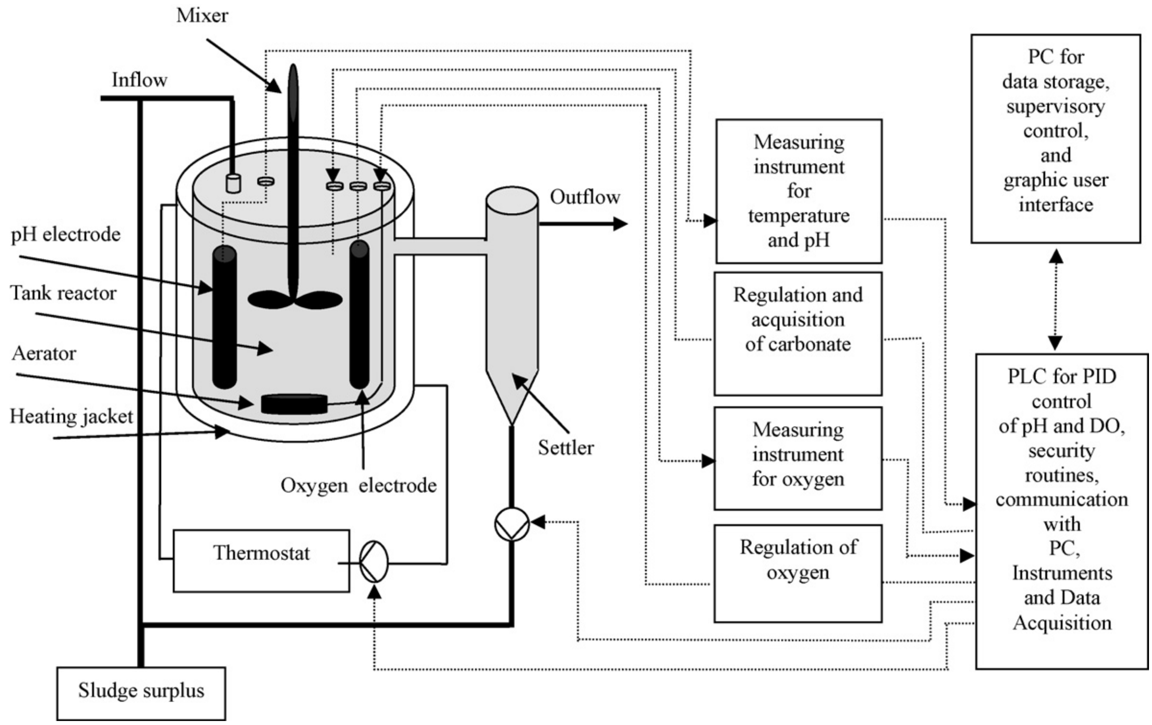


Fig. 2. Schematic diagram of the instrumentation and control system of the activated sludge reactor.

Table 1
Composition of the synthetic substrate solution for the BRDR

Compound	Unit	Concentration
$(NH_4)_2SO_4$	mg N/L	1179
$MgSO_4{\cdot}7H_2O$	mg Mg/L	6.00
K_2HPO_4	mg P/L	73.2
KH_2PO_4	mg P/L	73.2

The reactor was fed with a synthetic substrate, diluted to approximately 250 mg NH_4^+–N/L (see Table 1). The operational conditions were as follows: sludge recycling ratio = 0.6; mean hydraulic residence time (HRT) = 6 h; mean sludge age = 20 days. The concentrations of ammonium, nitrite and nitrate were measured daily using standardized experimental methodology [26].

For monitoring purposes, a graphic user interface [27] was designed using the MATLAB® Toolbox Guide [28]. This interface made it possible to obtain visual records every second of pH, DO, the percentage of time the air valve was open, and the Na_2CO_3 added.

2.2. SISO control

Linear PI controllers of pH and DO were implemented in the activated sludge and tuned to achieve similar responses to those estimated with predictive controllers (benchmarking).

The input–output transfer functions were obtained by applying stepped changes of 10% in the manipulated variable. Eq. (3) demonstrates the transfer function:

$$G(s) = \frac{K}{s+p}\,e^{-\tau s} \tag{3}$$

where K is the gain, p is the pole and τ is the delay. The parameters of Eq. (3) for DO concentration and pH are presented in Table 2.

A predictive controller was designed using the Matlab MPC toolbox (Model Predictive Control) [28] which minimises the following objective function:

$$J = \sum_{i=1}^{N_2}\left(y\left(\frac{t+k}{t}\right) - r\right)^2 + \lambda \sum_{k=0}^{N_u-1} \Delta u(t) \tag{4}$$

where y corresponds to the controlled variable, r is the set-point and u is the manipulated variable. The tuning parameters of this controller are N_2: prediction horizon, N_u: control horizon and λ: weighting factor. Simulations were done with the transfer functions to determine the tuning parameters with which the shortest settling time is obtained.

The PI controllers Eq. (5) were tuned by simulation. The proportional gain K_p and integral time T_i were determined, such that the response obtained was similar to that obtained with the MPC controller. The comparison index between the controllers was the ratio between the settling times [29]. The tuning parameters for the PI controllers of DO concentration and pH are presented in Table 2:

$$u(t) = K_p\left[e(t) + \frac{1}{T_i}\int_0^t e(\tau)\,d\tau\right] \tag{5}$$

Table 2
Parameters of the transfer function and SISO control

Controlled variable	Transfer function			MPC control			PI control	
	K	P	τ	N_2	N_u	λ	T_i	K_p
DO	1.035×10^{-3}	6.896	25.00	400	200	5×10^{-2}	23	113
pH	0.100	0.000	0.100	100	50.0	1×10^{-5}	1.0	200

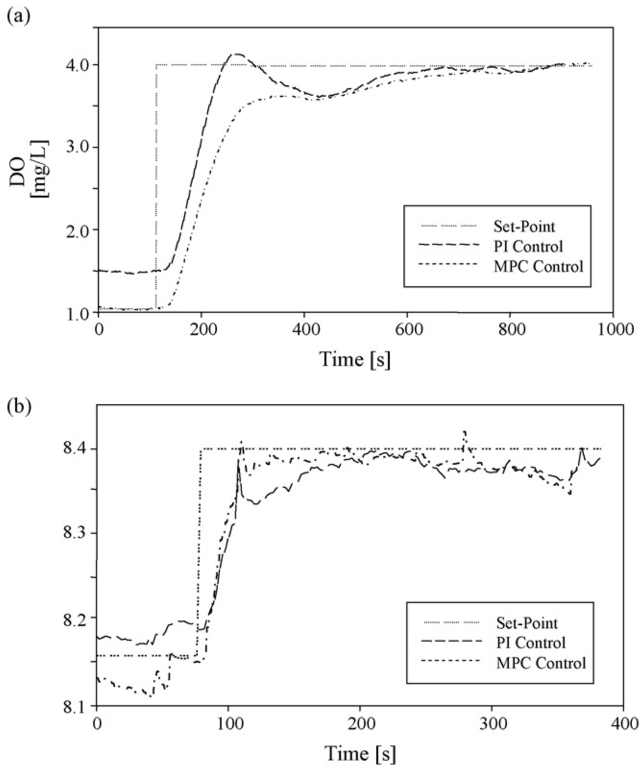


Fig. 3. SISO control for: (a) DO and (b) pH.

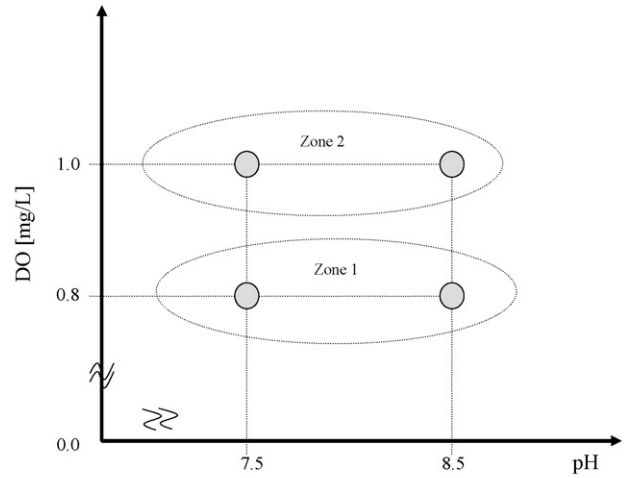


Fig. 4. Operation zones for the activated sludge reactor.

Fig. 3 presents the closed loop tests to compare the MPC and PID controllers. It may be observed that the settling time was similar with these two controllers, 600 [s]. Because the PI controller programmed in the Siemens S7-200 PLC presents greater availability than the MPC (programmed in PC), it was decided to implement the PI controllers as a SISO loop for DO and pH.

2.3. Self-tuning fuzzy multimodels for estimating efficiency indices

The pH and the DO concentration are the operating parameters which most affect partial nitrification, consequently they were chosen as entry variables for the fuzzy multimodels. The technique of first-order linear multimodels triggered by fuzzy logic tools was used [8] to find a relationship between the efficiency indices and the controlled variables (pH and DO). The on-line estimation of the efficiency indices, presented in Eqs. (6)–(11), is based on the following suppositions:

- In accordance with previous experimental studies [1,5,6,30], the ranges pH = [7.5–8.5] and DO = [0.8–1.0] mg O_2/L were selected as specific operating zones which promote partial nitrification to nitrite. Outside these ranges, the proposed model does not estimate efficiency indices.
- The first order linear model between the DO concentration and the efficiency indices varied slightly; it was therefore proposed to formulate two models for the DO: one at 0.8 mg O_2/L and another at 1.0 mg/L, as shown in Fig. 4. Both models were mixed using fuzzy logic techniques as described in Ragot et al. [24].
- The multimodels are based on experimental information acquired over a period of approximately eight months with pH and DO values obtained every second from the SCADA (Supervisory Control and Data Acquisition) system. Environmental conditions: $T = 23 \pm 1.1\,^{\circ}$C and autotrophic biomass concentration in the reactor = 1 g ± 0.2 mg VSS/L.

A total of four first-order linear models were identified. Two were for estimating locally the ammonium degradation in each operating zone, $\hat{\alpha}_1(t)$ and $\hat{\alpha}_2(t)$, which depend on the estimation at the previous moment $\hat{\alpha}(t-1)$ and on the pH(t) at the current moment Eqs. (6) and (7):

$$\hat{\alpha}_1(t) = 0.06\,\mathrm{pH}(t) + 0.32\,\hat{\alpha}(t-1) + \delta_{1\alpha}(k),$$
$$\mathrm{DO} = 0.8\,\mathrm{mg/L} \quad \text{and} \quad 7.5 < \mathrm{pH} < 8.5 \tag{6}$$

$$\hat{\alpha}_2(t) = 0.04\,\mathrm{pH}(t) + 0.35\,\hat{\alpha}(t-1) + \delta_{2\alpha}(k),$$
$$\mathrm{DO} = 1.0\,\mathrm{mg/L} \quad \text{and} \quad 7.5 < \mathrm{pH} < 8.5 \tag{7}$$

The other two models were for estimating locally the nitrite accumulation in each operating zone, $\hat{\beta}_1(t)$ and $\hat{\beta}_2(t)$, which depend on the estimation at the previous moment $\hat{\beta}(t-1)$, and on the pH(t) at the current moment Eqs. (8) and (9):

$$\hat{\beta}_1(t) = 0.05\,\mathrm{pH}(t) + 0.33\,\hat{\beta}(t-1) + \delta_{1\beta}(k),$$
$$\mathrm{DO} = 0.8\,\mathrm{mg/L} \quad \text{and} \quad 7.5 < \mathrm{pH} < 8.5 \tag{8}$$

$$\hat{\beta}_2(t) = 0.04\,\mathrm{pH}(t) + 0.31\,\hat{\beta}(t-1) + \delta_{2\beta}(k),$$
$$\mathrm{DO} = 1.0\,\mathrm{mg/L} \quad \text{and} \quad 7.5 < \mathrm{pH} < 8.5 \tag{9}$$

$\delta_{i\alpha}(k)$ and $\delta_{i\beta}(k)$, with $i = 1,2$, are empirical fitting parameters updated with each new set (k) of experimental data. The procedure to find these empirical fitting parameters will be explained later.

The equations which take into account the new estimation of $\hat{\alpha}(t)$ and $\hat{\beta}(t)$ at the current moment depend on the local estimates given in Eqs. (6)–(9), and on the dissolved oxygen concentration, which is described in the following Takagi–Sugeno-type fuzzy multimodel [24]:

$$\hat{\alpha}(t) = \hat{\alpha}_1(t)\,\mu_1(\mathrm{DO}(t)) + \hat{\alpha}_2(t)\,\mu_2(\mathrm{DO}(t)) \tag{10}$$

$$\hat{\beta}(t) = \hat{\beta}_1(t)\,\mu_1(\mathrm{DO}(t)) + \hat{\beta}_2(t)\,\mu_2(\mathrm{DO}(t)) \tag{11}$$

μ_i with $i = 1$ and 2 correspond to the evaluation of the fuzzy membership function in the DO level present in the process, with values between 0 and 1, as shown in Fig. 5. These fuzzy multimodels are nonlinear differential equations.

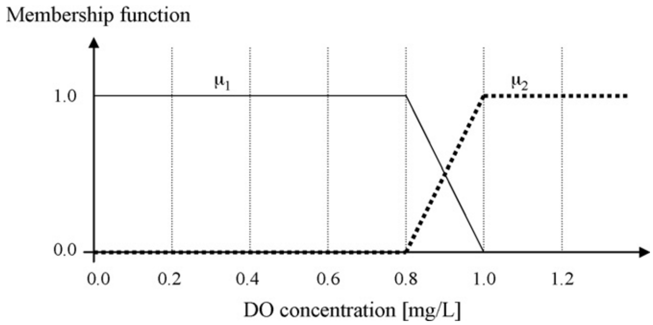


Fig. 5. Fuzzy sets for the models weightings (μ_1 and μ_2).

Since the fuzzy multimodels were designed at fixed environmental conditions (temperature and biomass concentration in the reactor), it was necessary to develop a system which would allow the models to be updated for slight disturbances. A self-tuning technique was proposed based on the efficiency indices obtained by experiment, as shown in Eqs. (12) and (13):

$$\delta_{i\alpha}(k) = \delta_{i\alpha}(k-1) + \eta_\alpha(\alpha(t) - \widehat{\alpha}(t)), \quad i = 1, 2 \tag{12}$$

$$\delta_{i\beta}(k) = \delta_{i\beta}(k-1) + \eta_\beta(\beta(t) - \widehat{\beta}(t)), \quad i = 1, 2 \tag{13}$$

η_α and η_β are empirical parameters of the calibration algorithm of the model while $\alpha(t)$ and $\beta(t)$ represent the experimental efficiency indices.

2.4. Supervisory control system

The supervisory control system proposed in this work is described in Fig. 6. The operation of the supervisor is based on an optimization layer located at decision support level, and is initiated by the off-line data gathering which permits the self-tuning of the δ_i parameters (Eqs. (12) and (13)). Once the fuzzy multimodels are updated, the function is maximised $\hat{\alpha}(t) + \hat{\beta}(t)$, as will be explained later. Once the optimum of pH* and DO* have been found in the decision support level, the supervisory system sets the SISO control references in the reactor (see Fig. 6) allowing the high α and β indices to be maintained.

In order to migrate smoothly to the new set-point calculated by the optimizer (pH*/DO* in Fig. 6), the supervisory system sets the regulatory control references with a constant turnover rate of 0.1 mg/(L min) and 0.1 min^{-1} for the DO and the pH, respectively.

The activated sludge reactor was operated with the supervisory control system over a period of 115 days. The environmental conditions were as follows: $T = 23 \pm 0.4\,^\circ$C and autotrophic biomass concentration in the reactor = [0.75–1.30] g VSS/L.

2.5. Optimization layer

As shown in Fig. 6 the optimization layer is based on the multimodel estimation of $\hat{\alpha}(t)$ and, using an exhaustive search algorithm that maximizes the objective function: $Z \to 2$ (Eq. (14)) for all combinations of pH and DO. The execution of the heuristic optimization algorithm (Fig. 6) was subjected to certain operational constraints (see Eq. (14)):

$$\begin{aligned} &\text{Maximize}\{Z = \hat{\alpha} + \hat{\beta}\} \\ &\text{subject to} \quad 7.5 \le \text{pH} \le 8.5 \\ &\qquad\qquad\quad 0.8 \le \text{DO} \le 1.0 \\ &\qquad\qquad\quad 0.9 \le \hat{\alpha} \le 1.0 \\ &\qquad\qquad\quad 0.8 \le \hat{\beta} \le 1.0 \end{aligned} \tag{14}$$

The heuristic optimization technique [31] consisted in the creation of a fine search net, dividing the search variables (DO and pH) into small increments. This net was then evaluated to obtain all the steady-state α and β values as well as the respective value of the objective function (Eq. (14)). The advantage of this algorithm is that it always finds the overall optimum in a certain search area. The net was generated by dividing the search area from 7.5 to 8.5 for pH, and from 0.8 to 1.0 for DO—in increments of 0.01 for each variable, so that the complete search requires 20,000 evaluations of the objective function (see Figs. 7 and 8), which were conducted in time intervals of less than one minute using MATLAB® 6.5 on a Pentium 4 PC at 2.4 GHz. The heuristic optimization algorithm was performed only when the multimodels were updated.

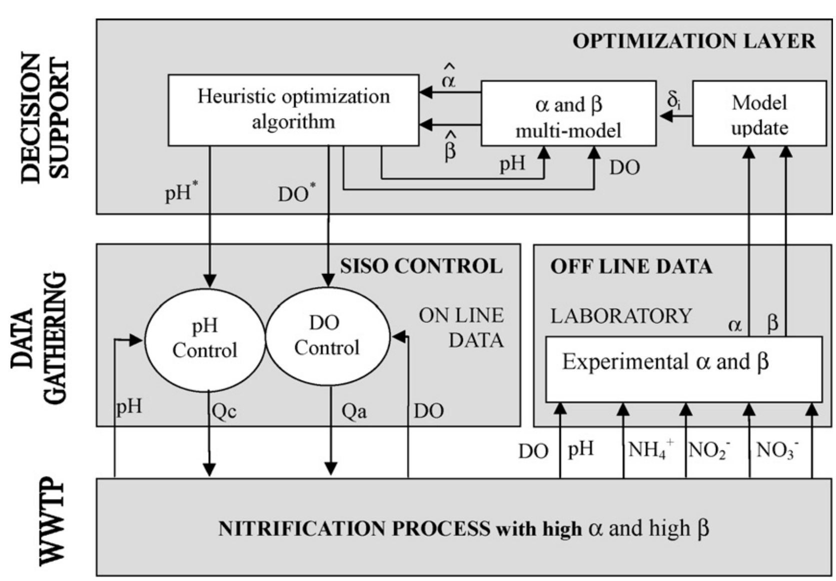


Fig. 6. Schematic diagram of the supervisory control system.

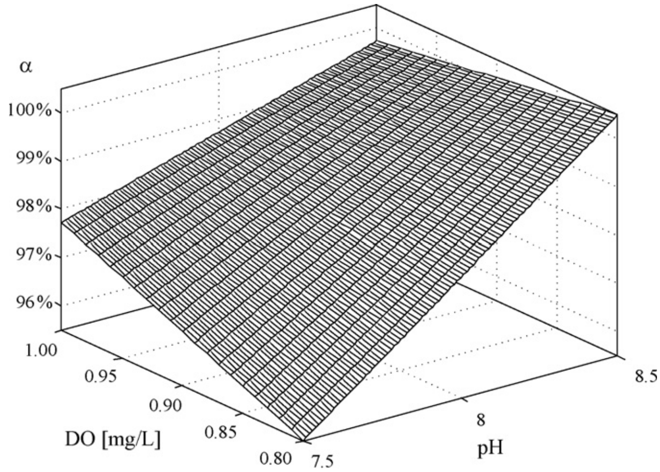


Fig. 7. Response surface for α according to the fuzzy multi-model.

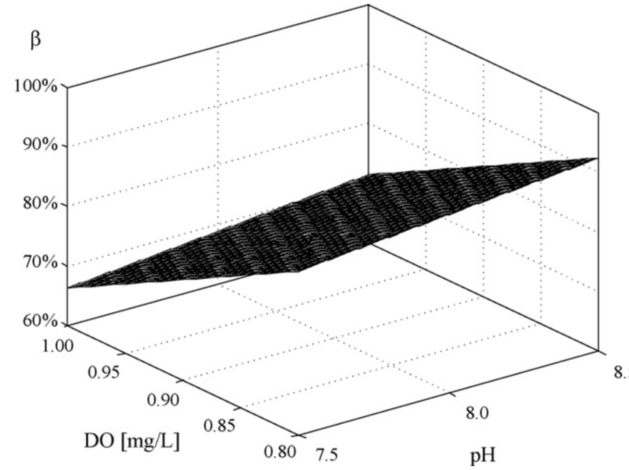


Fig. 8. Response surface for β according to the fuzzy multi-model.

3. Results and discussion

3.1. Fuzzy multimodels for estimating efficiency indices

In Figs. 9 and 10, experimental and calculated efficiency indices are charted over a period of 100 days. It is observed from calculated values that the response of α resembled that of a first-order linear system when it was excited with a step input. While the DO remained constant, there was a strong correlation between α and pH value, enabling the use of linear-system identification techniques. Using the available experimental data, scattered values were eliminated and low-pass filters were applied to the α values

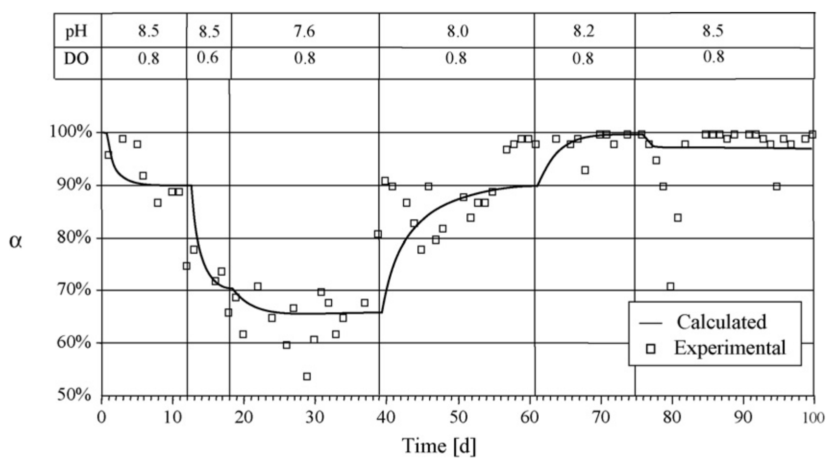


Fig. 9. α calculated with the fuzzy multi-model using the stored data.

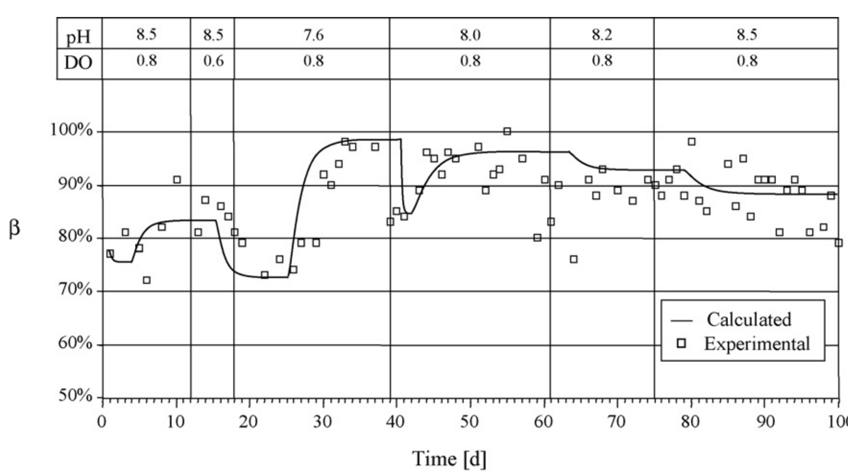


Fig. 10. β calculated with the fuzzy multi-model using the stored data.

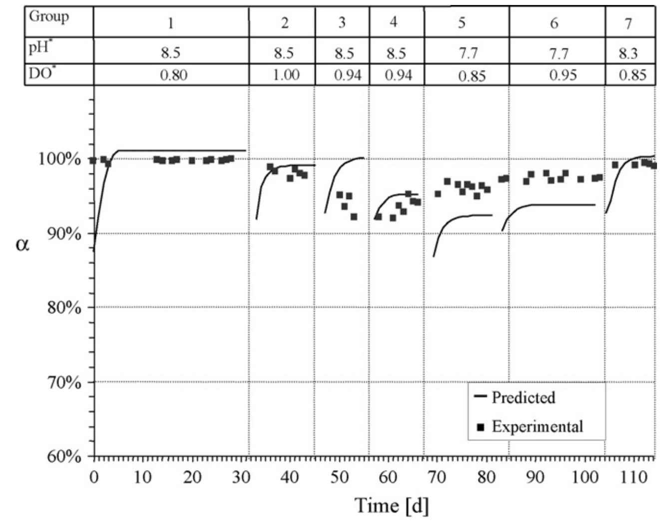


Fig. 11. Values of α achieved with the supervisory control system in an activated sludge reactor.

in such a way that the continuation of the curve could be clearly observed. The results are shown in Fig. 9, where α values calculated by the fuzzy multimodel estimated adequately the experimental data at different DO and pH values. The prediction of the β index by the fuzzy multimodel (see Fig. 10) was also satisfactory.

3.2. Supervisory control system

Figs. 11 and 12 show the performance of the supervisory control system with respect to the experimental efficiency indices at steady state, considering only experimental data with a fluctuation below 5%. On-line estimates of α and β were performed and the model parameters were updated with each new combination of experiment analyses. Above are shown the pH* and DO* set-points, which were generated each time the supervisory control system performed a new optimization resulting from a model update and set in the reactor during the whole time delimited in the seven groups. Note that since the optimum set-points remained the same after the self-tuning of the model at 56 days, groups 3 and 4 have identical pH* and DO*.

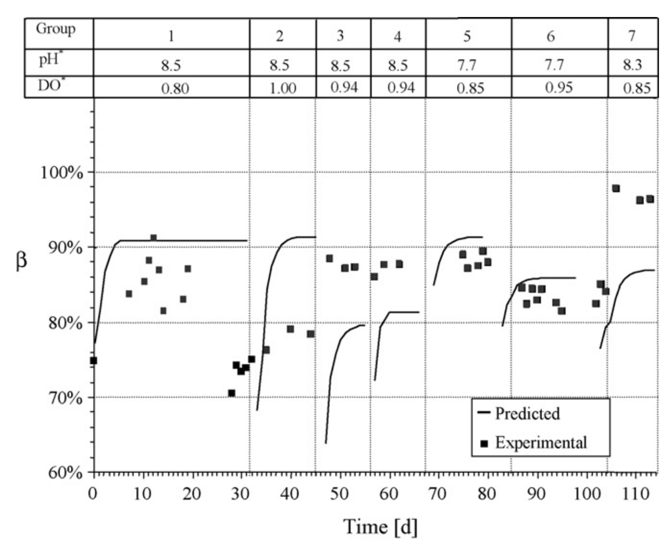
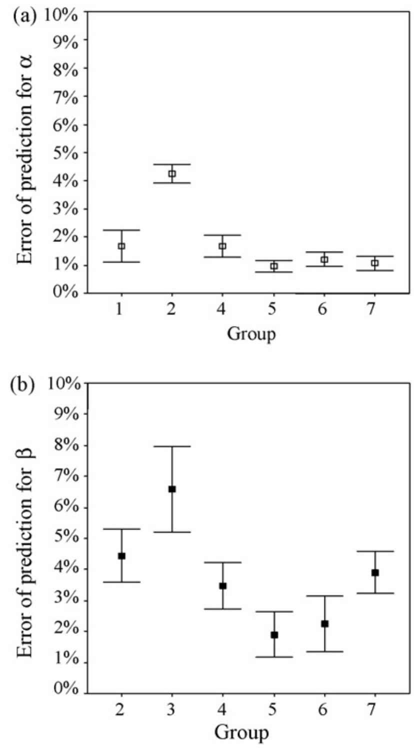


Fig. 12. Values of β achieved with the supervisory control system in an activated sludge reactor.



(c)

Group	pH*	DO*
1	8.5	0.80
2	8.5	1.00
3	8.5	0.94
4	8.5	0.94
5	7.7	0.85
6	7.7	0.95
7	8.3	0.85

Fig. 13. Error of fuzzy model predictions for: (a) α and (b) for β. At different operational conditions (c).

Although the supervisory system can estimate the efficiency indices, the most important result of this work was to obtain high nitrite accumulation, and simultaneously a low ammonium-nitrogen content in the effluent. Figs. 11 and 12 show that the supervisory control caused a slight reduction in the high degradation of ammonium α between groups 1 and 5 resulting in an increased accumulation of nitrite β. Campos et al. [32] and Ruiz et al. [33] report $\alpha > 85$ and β ranging from 50% to 65% for nitrification in an activated sludge reactor without a supervisory control system, while in this work the use of an optimization layer in the decision support level (Fig. 6) resulted in $\alpha > 95\%$ and $\beta > 80\%$ (Figs. 11 and 12) on a long-term basis.

Fig. 11 shows that the supervisory control was able to maintain experimental α close to 100% during most of the operation. Because of the dynamic nature of the fuzzy multimodel, which is based on differential equations, the estimated α presented a transient profile before reaching the steady state. As shown in Fig. 11, from day 75 onwards the set-points of pH* and DO* maintained a stable α, around 98%, with values predicted by the multimodel very close to those of the experiment at steady state (error lower than 5%). Fig. 12 shows that the quality of the fuzzy multimodel β prediction was initially (groups 1–3) lower than the experimental α shown in Fig. 11; however, the self-tuning technique improved the β prediction of groups 2–6. In groups 6–7 the poorer quality of β prediction was compensated by a better quality of α prediction. From day 45 onwards, the supervisory control was able to reach and maintain mean β indices higher than 85%, and during days 105–115 even exceeded 95%.

The multimodel was designed for on-line estimation, so disturbances in the on-line input data can occasionally generate predictions over 100% for α and β, as can be seen in Figs. 11 and 12.

In Fig. 13 the prediction errors of α and β at steady state are compared for different updates of the fuzzy multimodels. Fig. 13(a) presents the prediction errors for α in groups 1–7. Group 3 was excluded because of insufficient experimental data. As shown, both the mean value and the standard error deviation for α were low and constant, between 1% and 2% (except for group 2). Fig. 13(b) presents the prediction errors for β in groups 2–7; group 1 was also excluded due to scattering. The mean error for β was maintained below 7% and the quality of β predictions improved during the model updates (see groups 3–6 in Fig. 13(b)). Considering that the multimodels were designed in slightly different environmental conditions to those used during operation of the activated sludge reactor with the supervisory control (see Sections 2.3 and 2.4), the self-tuning technique applied during model updates resulted in the satisfactory prediction of α and β.

Analysis of the DO–pH operating scenarios was similar to the strategy of Rodríguez-Roda [12], but using an exhaustive search algorithm to evaluate all the feasible values of DO and pH. The DO and pH values which maximize α and β simultaneously were set in the reactor by the supervisory control system. This study therefore contributes to the formulation of a structurally simple non-linear adaptable model with a strategy which takes advantage of the availability of on-line and off-line data and the use of an exhaustive search algorithm to obtain a stable partial nitrification process with high efficiency indices.

To apply the proposed supervisor system on an industrial scale, certain deficiencies in the transfer of mass must be considered, for example incomplete stirring in the aeration tank. In this case, it is feasible to complement the multimodels with others valid for different sections of the reactor.

4. Conclusions

A supervisory control system was developed using Takagi–Sugeno fuzzy multimodels with a simple structure and was based on an optimization layer (exhaustive search algorithm). During 3 months of operation the supervisory control generated optimum pH and DO set-points in order to maintain an activated sludge reactor operating at stable partial nitrification with ammonium degradation (α) and nitrite accumulation (β) higher than 95% and 80%, respectively.

The Takagi–Sugeno fuzzy multimodels were designed to estimate α and β on-line during the process, updated with off-line experimental data. These multimodels predicted the α and β indices at steady state with an error of less than 7% for an activated sludge reactor.

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