FUZZY SUPERVISORY CONTROL AND SUBSTRATE ADDITION TO IMPROVE EFFLUENT QUALITY IN AN ACTIVATED SLUDGE WASTEWATER TREATMENT PLANT

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Abstract

In this paper, we explore the combination of two control strategies for activated sludge wastewater treatment plants. From the plant configuration proposed by the Benchmark of the European group COST 624, first a fuzzy supervisory control which adequate the parameters of two local controllers is described and applied, then it is combined with a control strategy previously developed: extra substrate addition. Finally, different control strategies are compared via simulations.

1 Introduction

Clean water is essential for the environment. The endless enlargement of human population and economic activities demands an increase on the utilization of this no renewable resource; in the future, it will be required to treat and re-use most of the industrial wastewater. Hence, the development of new and better wastewater treatment plant is a big need. Activated sludge process, which is an aerobic one, is commonly used for treatment of urban and industrial wastewater.

This kind of plant was the first process, based on biological microorganisms, introduced to clean water [1] and is still the first choice for municipal wastewater treatment plants. Due to process complexity, there exists a big interest to apply computational intelligence techniques for its modeling and control [2, 3]. The goal of this paper is to improve the performance of the process combining a new structure of intelligent control for regulation of an activated sludge wastewater treatment plant along with the strategy of extra substrate addition in the influent [14].

Based on the proprieties of the process and in the characteristics of the influent, we developed a fuzzy supervisory control, which regulates the set point for the dissolved oxygen control along with the design parameters of the local controller. Besides, the supervisor increases or reduces the external feedback flow in order to compensate the dilution produced when rain or storm is present.

The extra substrate addition has been already tested for this process [14] and it improves the effluent quality substantially. This strategy is implement with the fuzzy supervisor to improve as much as possible the effluent quality, and eliminate if possible, the effluent violations of the maximum limits for pollutants.

2. Process Description

The diagram of a typical aerobic treatment plant is presented in Fig. 1. It corresponds to the benchmark of the European group COST 624, which aims to compare control strategies of activated sludge processes in wastewater treatment plants [4]. The two main components are: the bioreactor, which usually can be modeled by five sections and the settler, where sedimentation takes place, modeled by 10 layers.

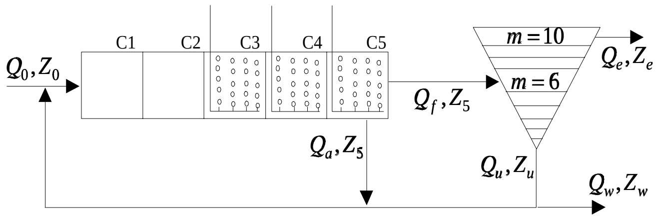


Fig. 1 – Process Scheme

The first two compartments in the bioreactor, where denitrification takes place, are non-aerated and the last tree compartments (nitrification process) are aerated. Q_0 and Z_0 are the flow rate and the concentrations of the plant influent (perturbations); Q_f and Z_5 are the flow rate and the concentrations at the bioreactor output; Q_e and Z_e are the flow rate and the concentrations of the plant effluent; Q_w and Z_w are the flow rate and the concentrations of the sludge wastage, and Q_a is the internal recycle flow rate. To achieve denitrification of the effluent with this structure (first anoxic compartments, then aerated ones), an internal recycle flow rate Q_a is considered. All the flow rates used in the model are in m^3/day.

The main variables of this process are

S_S	Readily biodegradable substrate.
$X_{B,H}$	Active heterotrofic biomass.
$X_{B,A}$	Active autotrofic biomass.
S_O	Dissolved oxygen.
S_{NO}	Nitrate and nitrite nitrogen.
S_{NH}	Amoniacal nitrogen

The global mathematical model for this process requires 145 nonlinear differential equations, obtained by calculating mass balances for the five sections of the bioreactor and the 10 layers of the settler, where no biological reaction is considered.

2.1 Automatic Control Structure

In [4], are proposed two local control loops are proposed : a) dissolved oxygen control in section 5, by means of the aeration speed for the same section; and b) nitrates and nitrites control in section 2 by means of the internal feedback flow; however, in [14] an analysis of the process and a sensitivity analysis among several typical inputs and outputs of the process, define a new control loop that substitutes the control of nitrates and nitrites; it's implemented improving substantially the efficiency of the process; this one consists in the control of total nitrogen (S_{NH} + S_{NO}) in the section 5, by means of the addition of extra organic carbon (S_{AD}) as soluble substrate in the influente of the plant.

3. Control Strategy

In this paper, we extended to activated sludge wastewater treatment plants, the strategy already proposed for anaerobic ones [5].

3.1 L/A Structure

It is discussed in [6,7,8], and portrayed in Fig. 2.

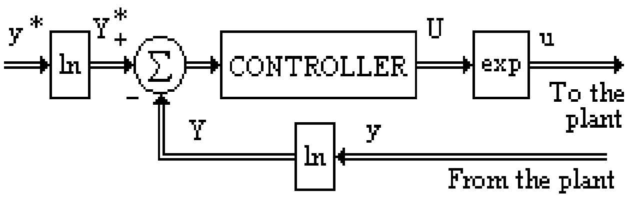


Fig. 2 - L/A Controller

This structure is based on the following transformations

- Logarithmic transformation

$$Y(t) = ln\, y(t), Y^*(t) = ln\, y^*(t), U(t) = ln\, u(t) \qquad (1)$$

- Exponential transformation

$$y(t) = exp\, Y(t), y^*(t) = exp\, Y^*(t), u(t) = exp\, U(t) \qquad (2)$$

where *y(t)* is the output, $y^*(t)$ is the set point, and *u(t)* is the control action.

These transformations allow to select any conventional control law and to obtain an L/A equivalent. In [9], a PI is used as follows

$$U_k = U_{k-1} + K_1(Y_{k-1} - Y_k) + K_2(Y_k^* - Y_k) \qquad (3)$$

with K_1 and K_2 the integral and proportional gains respectively.

The L/A equivalent of this control law is:

$$u_k = u_{k-1}\left(\frac{y_{k-1}}{y_k}\right)^{K_1}\left(\frac{y_k^*}{y_k}\right)^{K_2} \qquad (4)$$

The control law (4) offers different advantages, such as: a) It takes into account the physical process constraints (such as positivity), b) It does not require to know the mathematical model of the process.

3.2 Fuzzy PI Control

Nonlinear PI fuzzy control is described in [10] and the stability analysis is presented in [11]; the fuzzy algorithm use two input variables, error and rate of change of error (named rate for short), and one output variable. Its structure is shown in Fig. 3.

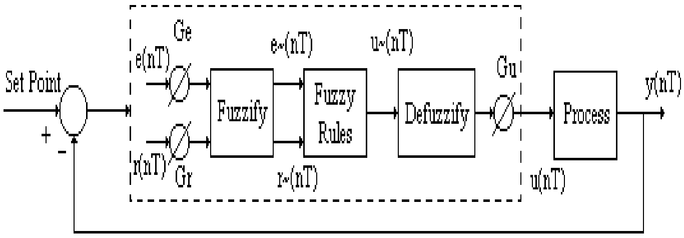


Fig. 3 – Fuzzy Controller

where y(nT), e(nT), r(nT) and u(nT) are the output, error, rate of change of error and input (output fuzzy controller) from the process; Ge, Gr and Gu are scalers for error, rate and output from the fuzzy controller; e~(n), r~(nT) and u~(nT) are the fuzzy sets corresponding to error, rate of change of error and output.

The fuzzy sets for the input variables are shown in Fig. 4., and the fuzzification for the fuzzy controller output is presented in Fig. 5.

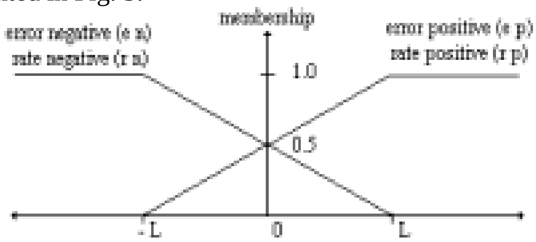


Fig. 4 - Fuzzy sets for the inputs

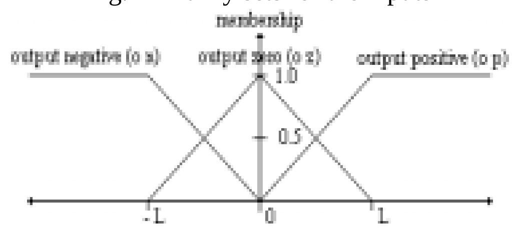


Fig. 5 - Fuzzy sets for the output

Hence, there are four fuzzy rules:

If error=ep AND rate=rp then output=on (r1)
If error=ep AND rate=rn then output=oz (r2)
If error=en AND rate=rp then output=oz (r3)
If error=en AND rate=rn then output=op (r4)

Since the AND operator is the minimum of two values, there are two possible conditions for each rule, and eight different combinations resulting from all rules evaluation [10].

The equation for defuzzification is

$$u(nT) = -\left\lfloor K_i * e(nT) + K_p * r(nT) \right\rfloor \qquad (5)$$

where

$$K_i = \frac{0.5 * L * Gu * Ge}{2L - Ge * |e(nT)|}, K_p = \frac{0.5 * L * Gu * Gr}{2L - Ge * |e(nT)|} \qquad (6)$$

$$If\ \ Gr * |r(nT)| \le Ge * |e(nT)| \le L$$

and $K_i = \dfrac{0.5 * L * Gu * Ge}{2L - Gr * |r(nT)|}, K_p = \dfrac{0.5 * L * Gu * Gr}{2L - Gr * |r(nT)|}$ (7)

$If\ Ge * |e(nT)| \le Gr * |r(nT)| \le L$

3.3 Fuzzy PI L/A Control

Next step it is the fuzzification of the control actions. Then, the algorithm described in previous section is applied to the L/A technique described on section 3. Both algorithms use a PI expression, equations (5) and (6) in the case of L/A and equation (7) for fuzzy controller. Mathematically, they are the same because the error and rate of change of error are used; the only difference is the way to calculate the proportional and integral gains, which are constant for the L/A technique and time-variant for the fuzzy case.

Hence, the output Fuzzy-PI-L/A controller is described as:

$$u_k = u_{k-1} \left(\frac{y_{k-1}}{y_k} \right)^{K_{1\_f}} \left(\frac{y_k^*}{y_k} \right)^{K_{2\_f}} \quad (8)$$

where K_{1_f} and K_{2_f} are calculated respectively by (6) and (7).

3.4 Fuzzy Supervisory Control

Fuzzy supervisory control is a hierarchical controller strategy with the supervisor at the highest level. The supervisor can use any available data from the control system to characterize the system's current behavior and to adapt the controller parameters. The fuzzy supervisory control can be implemented using a functional fuzzy system.

Functional fuzzy systems [12] are a special case of fuzzy systems with the rules on the form:

If u_i is $A_1^{\,j}$ and u_2 is $A_2^{\,k}$ and,…,and u_n is $A_n^{\,l}$ then $b_i=g_i(.)$ (9)

where "." represents the argument of the function g_i and the b_i are not output membership function centers. The premise of this rule is defined with linguistic terms like for the standard fuzzy system. The consequent is different, instead of linguistic terms with an associated membership function, we use a function $b_i=g_i(.)$, which does not have an associated membership function. The choice of this function depends on the application being considered. Virtually any function can be used (e.g., a linear equation, neural network mapping or another fuzzy system), which makes the functional fuzzy system very general. For the functional fuzzy system we can use an appropriate logical operation for representing the premise (e.g., minimum or product) and defuzzification may be obtained using

$$y = \frac{\sum_{i=1}^{R} b_i \mu_i}{\sum_{i=1}^{R} \mu_i} \quad (10)$$

where μ_i is the membership value defined as $\mu_i(u_1, u_2, \ldots, u_n) = \mu_{A_1^j}(u_1) * \mu_{A_2^k}(u_2) * \ldots * \mu_{A_n^l}(u_n)$

One way to view the functional fuzzy system is as a nonlinear interpolator between the mappings that are defined by the consequents of the rules.

4. Plant Applications

These applications were done on the basis of the benchmark [4] developed by the European program COST 624 for the evaluation of control strategies in wastewater treatment plants. The benchmark is based on the most common wastewater treatment plant: a continuous flow activated sludge plant, performing nitrification and pre-nitrification. The Benchmark, independent from simulation environment, defines a plant layout, a simulation model, influent loads, test procedures and evaluation criteria. We will conform us strictly to the benchmark methodology especially for the process and control performances evaluation. The implementation was performed under a Matlab / Simulink environment, and simulator validity was tested according to the operating point and open loop simulation given in the benchmark description. We consider three different weather conditions, as described in [13], and include in Appendix A1

The applications are performed as follows. First the fuzzy supervisory control is described and tested using the tow originals control loops of the benchmark (dissolved oxygen control and nitrates and nitrites control), and finally the supervisor is implemented along with the strategy of extra substrate addition in the influent.

4.1 Simulation Data

- Simulated Time: 32 days. (All the simulations have this structure: the first 4 days of the simulation use constant influent data, the next 14 days use Dry weather data (see appendix A1) and the last 14 days of the simulation use data of the desired weather).
- The most important parameters are [12]:
  Total biological volume (bioreactor) : 6,000 m^3
  Settler .- volume = 6,000 m^3, depth = 4 m.
  Influent flow rate (average) : 18,446 m^3/day
  Wastage flow rate : 385 m^3/day

4.2 Fuzzy Supervisory Control of the Activated Sludge Process

The supervisor's first part is designed based on NH concentration tracking. The main reason for this choice is that the concentration of ammonium in the last section of the bioreactor is an indicator of the relationship between the level of nitrification and denitrification that is occurring at present inside the bioreactor. Then, when the ammonium concentration is low this means that we have high nitrification and we need to reduce the concentration of dissolved oxygen to increase denitrification. Hence the fuzzy sets are defined as

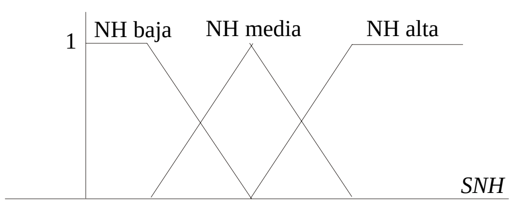


Fig. 6 – Input Membership Functions

The respective rules are:

- If *SNH* is *NHbaja* then Ref_DO = Rb, Ki_DO=Kib, Kp_DO=Kpb
- If *SNH* is *NHmedia* then Ref_DO = Rm, Ki_DO=Kim, Kp_DO=Kpm (11)
- If *SNH* is *NHalta* then Ref_DO = Ra, Ki_DO=Kia, Kp_DO=Kpa

where Ref_DO is the *DO* set-point, Ki_DO is the integral gain of the controller, and Kp_DO is the proportional gain of the controller. Three fuzzy PI L/A controllers are used, for three different operation regions.

The supervisor's second part is designed based on the characteristics of the influent. The variable *"storm relactión"* *SR*, is defined as $SR(t)=Q_0(t)/\ S_{NH,0}(t)$ and is utilized to identify influente with affected behavior for rain or storms. When the process receives an influent that has been affected by rain or storms gradually decay all the concentrations inside de bioreactor, and also the elimination of pollutants is reduced. The external recycle flow rate Q_r is varied in terms of *SR* to oppose the dilution effects. The fuzzy sets are defined as

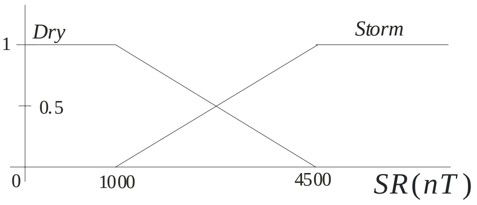
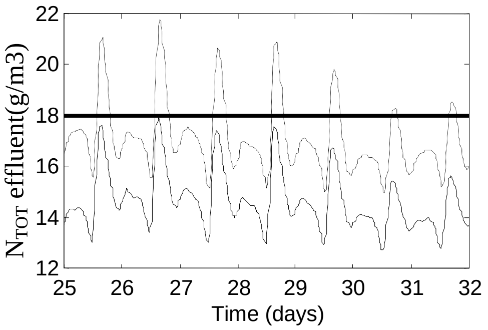


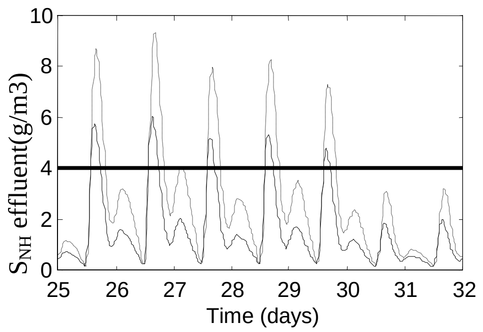
Fig. 7 – Input Membership Functions

In this case, the respective rules are:

- If *SR* is *Dry* then (12)
  $Q_r=Q_{r,d}$, Ki_SNO=Kid, Kp_SNO=Kpd, ΔRef_DO=0
- If *SR* is *Storm* then
  $Q_r=Q_{r,s}$, Ki_SNO=Kis, Kp_SNO=Kps, ΔRef_DO=Δ

This supervisor is implemented applying fuzzy PI L/A for the DO control and a fuzzy PI for the S_{NO} control [15]. Figure 8 presents the respective simulation results with "Dry weather". The original classic control is described in [4], employs constant set points and classic PI controllers.





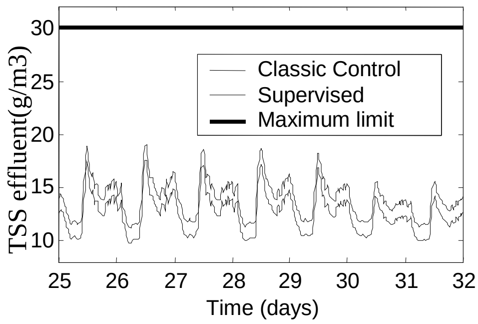


Figure 8 - Concentrations in the effluent comparing the results with original classic control and with supervised control for "Dry weather".

4.3 Substrate Addition

As described in [14], the addition of extra carbon in the influent of the plant, improve the effluent quality substantially. Now, the fuzzy supervisor described previously is implemented substituting the control of nitrates and nitrites in section 2, with the total nitrogen (S_{NH} + S_{NO}) control in the section 5, and the output of the supervisor's second part, only contains the corresponding to Q_r. A PI fuzzy with L/A is used for this new control loop, as is described in [14], with a set point of 10 gr/m^3; the manipulated variable is the quantity of extra readily biodegradable substrate added to the influent in gr/day.

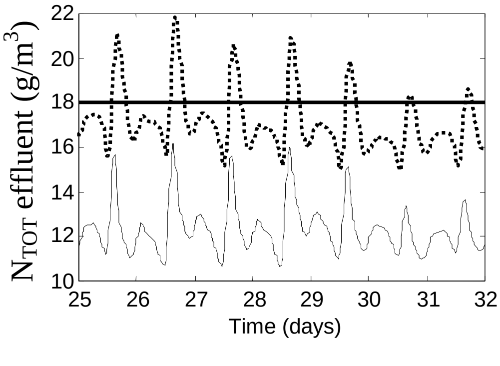
The saturation level for $(kla)_5$ (the manipulated variable in DO control) was increased to 480 day^{-1} (in [4] is reported as 240 day^{-1}) in order to observe the behavior of the system without saturation of this manipulated variable.

Two different set of tuned parameters are tested to illustrate the compromise between the effluent quality and the operational costs. In the first set of parameters (SIM1) we use the original supervisor's parameters and in the second one (SIM2) we propose to increase the external feedback flow on (12) and the DO set points on (11). The table 4.1 shows these values.

Table 4.1 – Parameters of the fuzzy supervisory control.

	Rb gr/m^3	Rm gr/m^3	Ra gr/m^3	$Q_{r,d}$ m^3/day	$Q_{r,s}$ m^3/day
SIM1	0.5	1.5	2.5	36,892	73,784
SIM2	1	2	3	92,230	18,446

Figures 9 and 10 presents the respective simulation results with "Dry weather" and in table 4.2, 4.3 and 4.4 we present the comparison of performances indexes [4] of the simulations for the tree weather conditions. In appendix A2 we present a list of the meaning of these performance indexes according with [4].



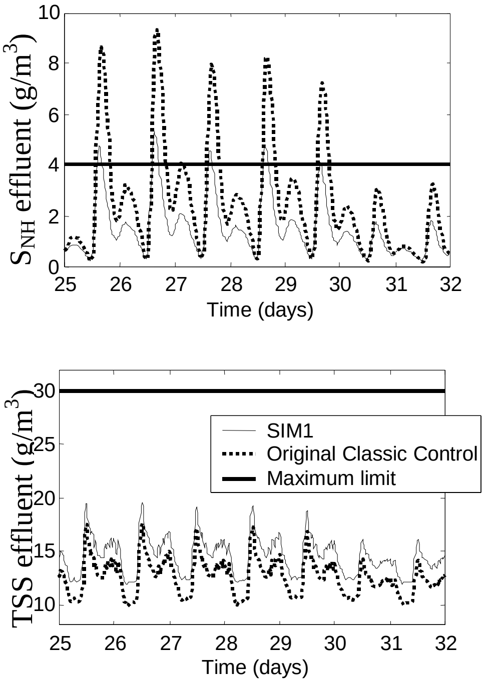


Figure 9 - Comparing the results with original classic control and with fuzzy supervised control (SIM1) + extra substrate addition "Dry weather".

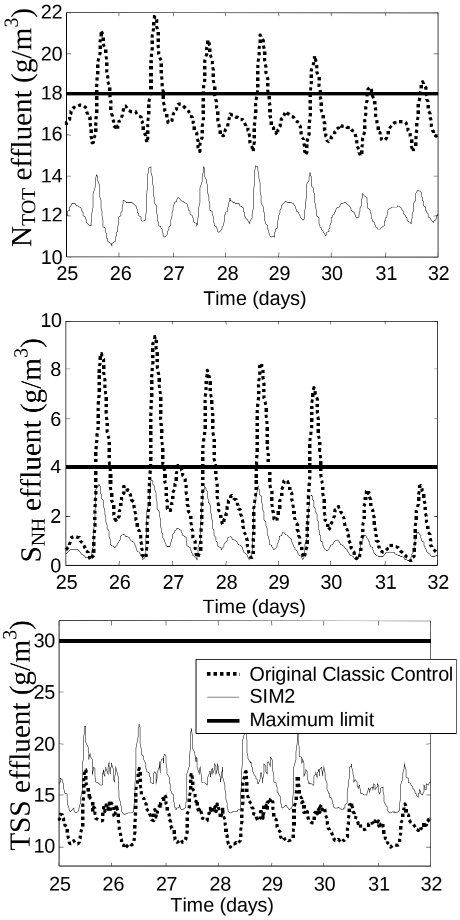


Figure 10 - Comparing the results with original classic control and with fuzzy supervised control (SIM2) + extra substrate addition "Dry weather".

Table 4.2 – Performance indexes of the simulations with "Dry weather".

	EQ	*Viol. Ntot,e*	*Viol. S_{NH},e*	*Viol. TSS,e*	*AE*	*PE*	*Plodos*	*SA*
Original Control	7,590	18.45%	18.01%	0%	7,242	1,497	2,441	n/a
Supervisor Control	6,822	0%	10.27%	0%	6,968	2,339	2,273	n/a
SIM 1	6,014	0%	6.85%	0%	7,120	2,966	2,414	525
SIM 2	6,091	0%	0%	0%	7,400	5,180	2,274	507

Table 4.3 – Performance indexes of the simulations with "Rain weather".

	EQ	*Viol. Ntot,e*	*Viol. S_{NH},e*	*Viol. TSS,e*	*AE*	*PE*	*Plodos*	*SA*
Original Control	9,097	12.35%	28.13%	0%	7,168	1,913	2,358	n/a
Supervisor Control	8,385	0%	10.27%	0%	7,056	2,974	2,134	n/a
SIM 1	8,196	0%	8.93%	0%	7,177	3,193	2,136	176
SIM 2	8,289	0%	2.23%	1.34%	7,466	4,727	2,049	222

Table 4.4 – Performance indexes of the simulations with "Storm weather".

	EQ	*Viol. Ntot,e*	*Viol. S_{NH},e*	*Viol. TSS,e*	*AE*	*PE*	*Plodos*	*SA*
Original Control	8,368	16.67%	27.23%	0.30%	7,285	1,766	2,607	n/a
Supervisor Control	7,594	0%	13.39%	3.27%	7,081	2,719	2,410	n/a
SIM 1	7,108	0%	8.48%	3.27%	7,288	3,073	2,498	399
SIM 2	7,158	0%	0%	3.13%	7,590	4,967	2,393	385

From the simulation results, we observe that according with the effluent quality (*EQ*) and the violations, the best performance is obtained in "SIM1" and "SIM2", but they also show the highest aeration energy (*AE*) and the highest pumping energy (*PE*). The violations to total nitrogen (*Ntot*) are eliminated easily but for ammonium (S_{NH}) only with the increase of the external feedback (SIM2) is possible to avoid it.

5. Conclusions

The combination of two different control strategies was tested to improve effluent quality. A fuzzy supervisory control have been described and implemented; this supervisor eliminates the violations on total nitrogen and reduces approximately to the middle the violations on ammonium. Finally, a new control loop previously developed is implemented along with the fuzzy supervisor: the extra substrate addition.

The combination of these two control strategies improves the effluent quality and reduces even more the violations on ammonium (SIM1). A final modification of the supervisor's parameters (SIM2) eliminates all the violations for the "Dry weather" influent, and in the remaining weather influents the violations never surpass 4%. However, the operational costs rise considerably and it's more expensive to improve the effluent quality.

It is difficult to make a good comparison between the operational costs of the simulations that employs the extra substrate addition and that ones that does not employ it. However, we must to have in mind that our first objective is always the improvement of the effluent quality at any cost.

Have been possible to increase the external feedback flow and with this eliminate the ammonium violations because the extra substrate addition reduces the nitrates and nitrites concentration in the effluent; without the extra substrate addition an increase of the external feedback flow produces violations on total nitrogen because this flow has the highest concentrations of nitrates and nitrites of all the process components.

As future work

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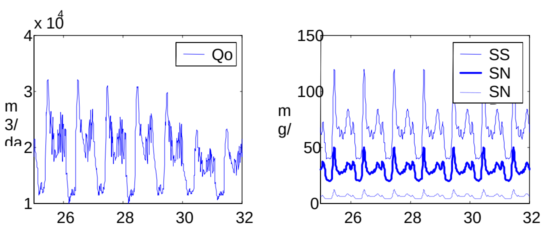
Appendice

A1 – Influent composition



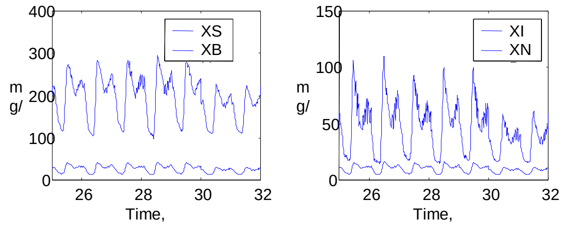


Figure A1.1 - Influent Composition for "Dry weather".

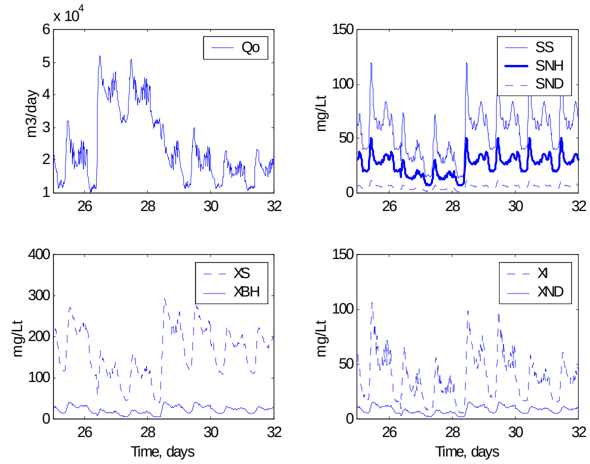


Figure A1.2 - Influent Composition for "Rain weather".

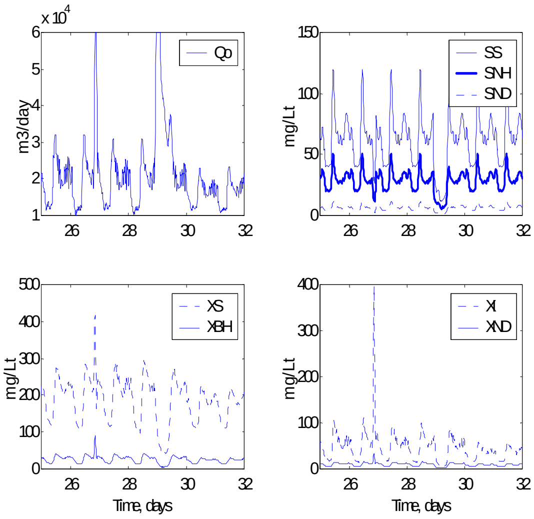


Figure A1.3 - Influent Composition for "Storm weather".

A2.- Performance Index for the Process Assessment.

EQ : Effluent Quality, (no units)

Viol. *Ntot,e* : Violations to maximum limit for total nitrogen in effluent, (% of time)

Viol. S_{NHt},*e* : Violations to maximum limit for ammonia in effluent, (% of time)

Viol. *TSS,e* : Violations to maximum limit for total suspended solids in effluent, (% of time)

AE.: Aeration Energy, (KW*hr/day)

PE : Pumping Energy, (KW*hr/day)

Plodos : Sludge production to be disposed, (Kg/day)

SA : Extra substrate added (not included in [4]), (Kg/day)