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

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Keywords – Fuzzy Control, Process Control, Biotechnological Process

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.

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](image)

The first two compartments in the bioreactor, where denitrification takes place, are non-aerated and the last three compartments (nitrification process) are aerated. \(Q_0\) and \(Z_0\) are the flow rate and the concentrations of the plant influent (perturbations); \(Q_1\) and \(Z_1\) 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; \(Q_a\) and \(Z_w\) are the flow rate and the concentrations of the sludge wastage, and \(Q_{ir}\) 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 \(Q_{ir}\) 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.
- \(X_{BH}\), Active heterotrophic biomass.
- \(X_{BA}\), Active autotrophic biomass.
- \(S_o\), Dissolved oxygen.
- \(S_{NO}\), Nitrate and nitrite nitrogen.
- \(S_{NH}\), Ammoniacal 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], 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.

\[ y^{*}(t) = \ln y(t), y^{*}(t) \quad (1) \]

3.2 Fuzzy PI Control
Nonlinear PI fuzzy control is described in [10] and the stability analysis is presented in [11]; the fuzzy algorithm uses 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.

\[ u(nT) = -[K_e * e(nT) + K_r * r(nT)] \quad (5) \]

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.
where "." represents the argument of the function 

use a function 

linguistic terms with an associated membership function, we 

fuzzy system. The consequent is different, instead of 

this rule is defined with linguistic terms like for the standard 

are not output membership function centers. The premise of 

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

\[
K_i = \frac{0.5 \cdot L \cdot Ge \cdot Ge_1}{2 \cdot L \cdot Gr \cdot |r(nT)|} \quad K_p = \frac{0.5 \cdot L \cdot Ge \cdot Gr}{2 \cdot L \cdot Gr \cdot |r(nT)|}
\]

(7)

\[
\text{If } Ge \cdot |r(nT)| \leq Gr \cdot |r(nT)| \leq L
\]

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.

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:

\[
\text{If } u_1 \text{ is } A_1^1 \text{ and } u_2 \text{ is } A_2^2 \text{ and ... and } u_n \text{ is } A_n^i \text{ then } b_i=g(.)
\]

(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 \(b_i=g(.)\), 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

\[
y = \frac{\sum b_i \mu_i}{\sum \mu_i}
\]

(10)

where \(\mu_i\) is the membership value defined as 

\[\mu_{1,2,...,n}(u_1,u_2,...,u_n) = \mu_{1}(u_1) \cdot \mu_{2}(u_2) \cdot \ldots \cdot \mu_{n}(u_n)\]

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 nitrate 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 m³
  - Settler - volume = 6,000 m³, depth = 4 m.
  - Influent flow rate (average) : 18,446 m³/day
  - Waste flow rate : 385 m³/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

1. NH baja
2. NH media
3. NH alta

Fig. 6 – Input Membership Functions
The respective rules are:

- **If** \( SNH \) **is** \( NH_{baja} \) **then** \( Ref_{DO} = R_b, \) \( Ki_{DO}=K_{ib}, \) \( Kp_{DO}=K_{pb} \)
- **If** \( SNH \) **is** \( NH_{media} \) **then** \( Ref_{DO} = R_m, \) \( Ki_{DO}=K_{im}, \) \( Kp_{DO}=K_{pm} \) \[(11)\]
- **If** \( SNH \) **is** \( NH_{alta} \) **then** \( Ref_{DO} = R_a, \) \( Ki_{DO}=K_{ia}, \) \( Kp_{DO}=K_{pa} \)

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 \( SR(t)=\frac{Q_0(t)}{S_{NH,t}} \) and is utilized to identify influent 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

![Input Membership Functions](https://via.placeholder.com/150)

In this case, the respective rules are:

- **If** \( SR \) **is** Dry then \( Q_r=Q_{rd}, \) \( Ki_{SNO}=K_{id}, \) \( Kp_{SNO}=K_{pd}, \) \( \Delta Ref_{DO}=0 \)
- **If** \( SR \) **is** Storm then \( Q_r=Q_{rs}, \) \( Ki_{SNO}=K_{is}, \) \( Kp_{SNO}=K_{ps}, \) \( \Delta Ref_{DO}=\Delta \)

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.

![Simulation Results](https://via.placeholder.com/150)

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/m3; the manipulated variable is the quantity of extra readily biodegradable substrate added to the influent in gr/day.

The saturation level for \( (kla)_S \) (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>
<thead>
<tr>
<th>Parameters of the fuzzy supervisory control.</th>
<th>( R_b ) gr/m(^3)</th>
<th>( R_m ) gr/m(^3)</th>
<th>( R_a ) gr/m(^3)</th>
<th>( Q_{rd} ) m(^3)/day</th>
<th>( Q_{rs} ) m(^3)/day</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIM1</td>
<td>0.5</td>
<td>1.5</td>
<td>2.5</td>
<td>36,892</td>
<td>73,784</td>
</tr>
<tr>
<td>SIM2</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>92,230</td>
<td>18,446</td>
</tr>
</tbody>
</table>

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].

![Simulation Results](https://via.placeholder.com/150)
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”.

<table>
<thead>
<tr>
<th></th>
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<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Control</td>
<td>7,590</td>
<td>18.45%</td>
<td>18.01%</td>
<td>0%</td>
<td>7,242</td>
<td>1,497</td>
<td>2,441</td>
<td>n/a</td>
</tr>
<tr>
<td>Supervisor Control</td>
<td>6,822</td>
<td>0%</td>
<td>10.27%</td>
<td>0%</td>
<td>6,968</td>
<td>2,339</td>
<td>2,273</td>
<td>n/a</td>
</tr>
<tr>
<td>SIM 1</td>
<td>6,014</td>
<td>0%</td>
<td>6.85%</td>
<td>0%</td>
<td>7,120</td>
<td>2,966</td>
<td>2,414</td>
<td>525</td>
</tr>
<tr>
<td>SIM 2</td>
<td>6,091</td>
<td>0%</td>
<td>0%</td>
<td>0%</td>
<td>7,400</td>
<td>5,180</td>
<td>2,274</td>
<td>507</td>
</tr>
</tbody>
</table>

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

<table>
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<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>Original Control</td>
<td>9,097</td>
<td>12.35%</td>
<td>28.13%</td>
<td>0%</td>
<td>7,168</td>
<td>1,913</td>
<td>2,358</td>
<td>n/a</td>
</tr>
<tr>
<td>Supervisor Control</td>
<td>8,385</td>
<td>0%</td>
<td>10.27%</td>
<td>0%</td>
<td>7,056</td>
<td>2,974</td>
<td>2,134</td>
<td>n/a</td>
</tr>
<tr>
<td>SIM 1</td>
<td>8,196</td>
<td>0%</td>
<td>8.93%</td>
<td>0%</td>
<td>7,177</td>
<td>3,193</td>
<td>2,136</td>
<td>176</td>
</tr>
<tr>
<td>SIM 2</td>
<td>8,289</td>
<td>0%</td>
<td>2.23%</td>
<td>1.34%</td>
<td>7,466</td>
<td>4,727</td>
<td>2,049</td>
<td>222</td>
</tr>
</tbody>
</table>

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

<table>
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<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>Original Control</td>
<td>8,368</td>
<td>16.67%</td>
<td>27.23%</td>
<td>0.30%</td>
<td>7,285</td>
<td>1,766</td>
<td>2,607</td>
<td>n/a</td>
</tr>
<tr>
<td>Supervisor Control</td>
<td>7,594</td>
<td>0%</td>
<td>13.39%</td>
<td>3.27%</td>
<td>7,081</td>
<td>2,719</td>
<td>2,410</td>
<td>n/a</td>
</tr>
<tr>
<td>SIM 1</td>
<td>7,108</td>
<td>0%</td>
<td>8.48%</td>
<td>3.27%</td>
<td>7,288</td>
<td>3,073</td>
<td>2,498</td>
<td>399</td>
</tr>
<tr>
<td>SIM 2</td>
<td>7,158</td>
<td>0%</td>
<td>0%</td>
<td>3.13%</td>
<td>7,590</td>
<td>4,967</td>
<td>2,393</td>
<td>385</td>
</tr>
</tbody>
</table>

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 (SNH) 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 approximatively 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 nitrates.
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, the authors suggest further research on the effectiveness of fuzzy control for wastewater treatment plants. They also highlight the importance of benchmarking control strategies in wastewater treatment plants.

References

Appendice

A1 – Influent composition