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A FUZZY-LOGIC BASED EXPERT SYSTEM FOR DIAGNOSIS AND CONTROL OF AN INTEGRATED WASTEWATER TREATMENT

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Abstract. A supervisory expert system based on fuzzy logic rules was developed for diagnosis and control of a lab- scale plant comprising anaerobic/anoxic/aerobic modules for combined high rate biological N and C removal. The design and implementation of a computational environment in LabVIEW for data acquisition, plant operation and distributed equipment control is described. The Fuzzy Logic toolbox for MATLAB was also used for the development of the fuzzy logic rule based system. The fuzzy rules were generated from quantitative and qualitative information, to identify the status of the plant operation and to decide the best commands to be sent to the final control elements to recover the stable operation in case of disturbances of the processes. A step increase in ammonia concentration from 20 to 60 mg N/L was applied during a trial period of 73 hours. Recycle flow rate from the aerobic to the anoxic module and by-pass flow rate from the influent directly to the anoxic reactor were the output of the fuzzy system that were automatically changed (from 34 to 111 L/day and from 8 to 13 L/day, respectively), when new plant conditions were recognized by the expert system. Denitrification efficiency higher than 85% was achieved 30 hours after the disturbance and 15 hours after the system response at an HRT as low as 1.5 hours. Nitrification efficiency gradually increased from 12 to 50% at an HRT of 3 hours. The system proved to properly react in order to set adequate operating conditions that timely led to recover efficient N and C removal rates.

Keywords: Anaerobic digestion, activated sludge, distributed supervision, expert system, fuzzy logic based system, nutrient removal.

1. Introduction

Conventional control methods are powerful when good analytical mathematical models are available to support their development and operation. This situation is uncommon in real processes. Particularly, the real-time control of wastewater treatment plants (WWTP) is a difficult but essential task, due to the lack of accurate dynamical models describing the process and reliable on-line instrumentation (Olsson and Newell, 1999). However, WWTP can be properly operated by specialized people, having knowledge about the process, though in practice, this know-how is essentially qualitative, empirical, and incomplete. The operation of a WWTP represents therefore a knowledge intensive task. In this regard, a system capable of giving all the possible information about the state of the process must be available in order to establish the basis of a diagnosis system integrating all the possible knowledge. This requirement is an important step to have successful control decisions (Patry and Chapman, 1989). Applications of knowledge-based systems to activated sludge processes are being widely studied (Chapman et al., 1989, Barnett et al., 1992; Ozgur et al., 1994). Most of systems are off-line Knowledge-Based Expert Systems (KBES) mainly diagnostic and advising tools to help process operators. Some KBES have been designed with the main purpose of online supervision, though the emphasis on real-time supervisor control is usually absent.

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Intelligent control, merging the tools of Artificial Intelligence into the control loop, whether in the direct digital control or in the supervision tasks, is a very promising technique. Fuzzy systems (allowing to process qualitative knowledge and to project qualitative-reasoning based controllers) and neural networks (allowing building parametric nonlinear models and controllers in a constructive way) are tools that already proved their capabilities (Müller et al., 1997; Du et al., 1999).

In biological wastewater treatments processes, efficient diagnosis and control systems are becoming more and more important due to the complexity of the bioprocesses involved. It is difficult to take into account the numerous factors that can influence the specific bacterial grow rate and its metabolic activity. Several types of disturbances may largely affect the operating conditions of a process, even in normal conditions. Data acquisition systems allow an overview of the state giving information about the operation. Monitoring comprises both hardware-based (sensors etc) and software-based (data-mining - from data to knowledge; software sensors allowing the estimation of non-measured variables). Particularly, for high rate combined N and C removal systems, monitoring is a very important feature in order to assure its control. The development of reliable online instrumentation is necessary due to the complexity of these integrated biological systems. Control and diagnosis of the biological systems are required to ensure the stable operation of a WWTP.

Baeza et al. (1999, 2000) reported the implementation of an expert supervisory system applied to a pilot WWTP comprising an anaerobic and nitrification/denitrification steps to remove nitrogen. A fuzzy control strategy was applied by Meyer et al. (2003) for the control of aeration in wastewater treatment plants with pre-denitrification. The implementation of expert systems based on fuzzy logic rules are described elsewhere (Carrasco et al., 2002; Puñal et al., 2002a and 2002b). Recently, especially attention to the expert supervision and control of anaerobic digestion processes is reported (Flores et al., 2000; Genovesi et al., 1999; Polit et al., 2002).

In this work, a supervisory expert system based on fuzzy logic rules was developed for the diagnosis and the control of a high rate lab-scale wastewater treatment plant used for organic mater and nitrogen removal. The fuzzy rules for diagnosis and control were integrated in the fuzzy logic rule based system, using quantitative and qualitative information, to identify the status of the plant operation and to decide the best commands to be sent to the final control elements to recover the stable operation in case of disturbances of the processes.

2. Methods

2.1. Plant Description

The lab-scale plant is based on a two-stage anaerobic/anoxic granular sludge bed reactors with 8 L and 8.5 L, respectively, working at 37ºC, followed by a 14 L nitrifying activated sludge tank, and a 2.5 L settler. A synthetic effluent, with a COD concentration of 2500 mg/L and a nitrogen concentration of 20 mg $N\text{-}NH_4^+$/L, was fed to an equalization tank, and then was pumped to the anaerobic module. When necessary, a by-pass from the equalization tank was directly applied to the anoxic stage to assure efficient denitrification. To test the expert based fuzzy logic system, a step increase on nitrogen concentration from 20 to 60 mg $N\text{-}NH_4^+$/L was imposed during a period of 73 hours. The nitrified effluent from the activated sludge tank was recirculated to the anoxic module. The remaining COD from anaerobic stage was used as the electron donor to the nitrogen removal in the anoxic one. The seed sludge for the anaerobic and the anoxic modules was anaerobic granular sludge collected at a UASB reactor treating brewery wastewater. A schematic layout of the process plant is shown in Fig. 1. Bioreactors were equipped with two biogas flowmeters (Ritter Apparatebau, GmbH, Bochum, Germany), a TFK 325 thermometer (WTW, Weilheim, Germany), two SensoLyt pH electrodes connected to a 296 R/RS monitor (WTW), an ORP Electrolyt 9816 probe (WTW), a ViSolid 700 IQ total suspended solids infrared probe and MIQ/S 184-H3 monitor (WTW), a TriOxmatic 690 dissolved oxygen probe (WTW). A Sequential Injection Analysis apparatus (Paralab, Porto, Portugal) was used for nitrite, nitrate and ammonium on-line analysis. Acetate was off-line measured by HPLC (Jasco, Japan) and converted to COD concentration values.

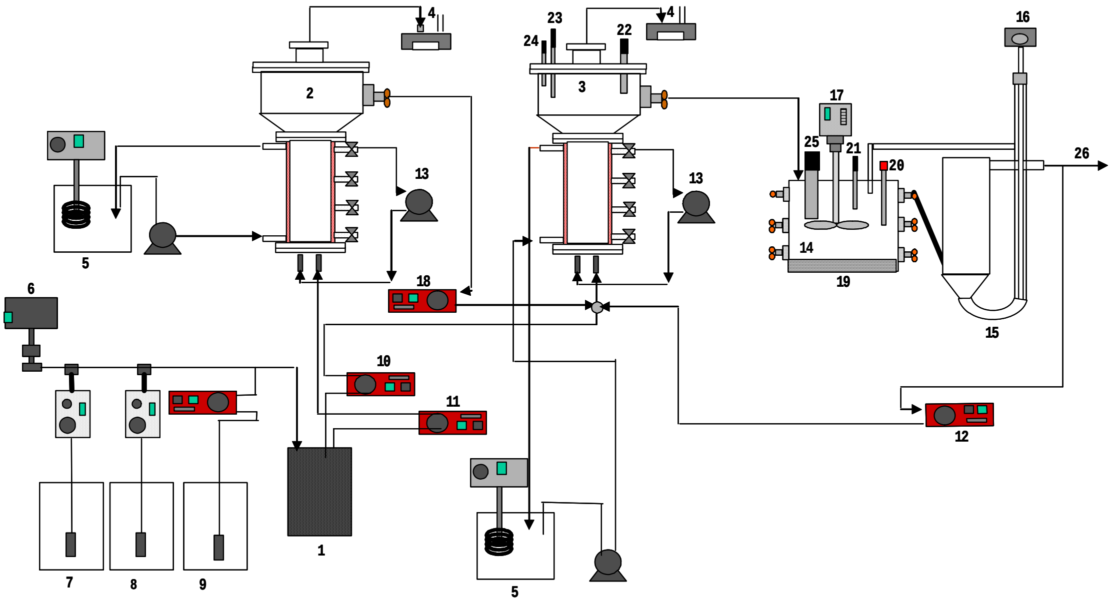

Fig. 1. Schematic layout of the plant: (1) equalization tank; (2) anaerobic reactor; (3) anoxic reactor; (4) gas flow-meters; (5) heat exchanger; (6) water regulation valve; (7) N source storage tank; (8) C source storage tank; (9) nutrient storage tank; (10) by-pass pump; (11) feeding pump; (12) external recycle pump; (13) internal recycle pumps; (14) aerated tank; (15) settler; (16) air pump, (17) stirrer; (18) anaerobic reactor to anoxic reactor pump; (19) aeration system; (20) dissolved oxygen probe; (21) pH probe; (22) ORP probe; (23) pH probe; (24) Pt-100 thermometer; (25) TSS probe; (26) outlet.

2.2. On-line sequential injection analysis of nitrogen forms

A Sequential Injection Analysis (SIA) system was developed to determine nitrite, nitrate and ammonia concentrations in the reactors. Nitrite was determined through formation of a reddish purple azo dye produced at pH 2.0 to 2.5 by coupling diazotized sulfanilamide with N-(1-naphtyl)-ethilinediamine dihydrochloride (APHA *et al.*, 1989). The reddish purple dye was detected spectrophotometrically at 540nm. The cadmium reduction method was used to determine nitrates. Nitrates are reduced to nitrite by using a copperised-cadmium column. The method is based on the quantification of both ions using two samples from the same point of the plant. First nitrites, them nitrates are analyzed. Nitrites and nitrates are detected from a range of 2 mgN-NO_2^- to 100 mgN-NO_2^- and 5 mgN-NO_3^- to 100 mgN-NO_2^-, respectively. 50 µl of sample is analyzed every 2 hours in triplicate.

Ammonium determination was based on the Nessler method (APHA *et al.*, 1989). 30 µl of sample was collected every 2 hours and ammonium concentration determined by detection of a yellow compound at 470 nm.

2.3. Software/Hardware

Three distributed network personal computers (PC) are used to monitor and control the plant operation: a supervisory computer responsible for data acquisition, data storage, equipment control, and hosting a web server; a second computer that controls the sequential injection analysis (SIA) system; a third local PC is used to command peristaltic pumps. The LabVIEW (National Instruments, USA) graphical development environment was used for the distributed software tasks of signal acquisition and processing, measurement analysis, data presentation, network and Data Socket communication, and Internet publication. Data are acquired periodically and recorded to Excel format files. The supervisory computer is equipped with a PCI 6024-E board (National Instruments, USA). Two PCL-718 boards (Advantech, Taiwan) are installed in the pumps control PC. The Fuzzy Logic toolbox for MATLAB (The Mathworks, Inc., USA) was used to embed the fuzzy logic system in LabVIEW.

2.4. Communications

A TCP/IP communication protocol is established between both supervisory and pumps control computers to remotely control the peristaltic pumps. The SIA system, although controlled from the SIA PC, can be also controlled from the supervisory PC, using the Data Socket protocol communication. Digital output signals are using to open/close the electrovalves of the SIA automated sampling system. The peak values are acquired and ionic concentrations determined and stored on the supervisory PC, also by the Data Socket protocol communication. The plant is equipped with in-line sensors (dissolved oxygen, temperature, pH, ORP and total suspended solids) interfaced to monitors interconnected in a BUS system. The supervisory computer acquires data from the monitors using the digital RS-485 protocol. Total suspended solids monitor provided analogue signals in the range of 4-20 mA. These signals were converted to 0-5 volts, which are acquired in the differential input mode through the PCI 6024-E board. Feeding pumps are controlled by a squared wave signal ranging from 0 to 5 volts issued from the PCI board. Biogas flow rates data are acquired using a digital counter of pulses generated by the gas flow meters.

2.5. The fuzzy rules based expert system

A supervisory expert system was built using the rule based structure IF “facts” THEN “conclusions (state or action)”. A rule derives operating knowledge from given facts, and is generated from the human knowledge. A fact is a description of the relationship between an input variable and its output variable. The rule based structure is made using the Fuzzy Logic toolbox for MATLAB. The rules are distinguished in five levels (very high, high, normal, low and very low), in order to be used by the diagnosis and control system. Fuzzy Rule is used respectively to build the control systems. The Fuzzy Rule Base algorithm embedded in MATLAB Fuzzy Logic toolbox has the following steps: the scalar inputs are transformed into memberships of fuzzy sets by fuzzifying functions; this information is given to the inference engine; then membership values are transformed into required scalar output variables by a defuzzification step.

The ranges of values corresponding to different levels of each variable are presented on Table 1 and Table 2. The main objective of the control system is to ensure low concentrations of nitrate, nitrite and COD in the plant effluent, actuating in the output variables of the fuzzy control system, which are the external recycle (R) and the by-pass (B) flow rates. The COD/N ratio at the influent of the anoxic reactor and the ammonium concentration in the influent of the plant are the two input variables considered in the control system.

Table 1. Labels of the variables used for the control system.

	V.L	L	N	H	V.H
$[N\text{-}NH_4^+]_{in}$ (mg/L)	0<N<10	10<N<30	30<N<50	50<N<80	80<N<120
COD/N	0<C/N<2	2<C/N<4	4<C/N<6	6<C/N<9	9<C/N<15

Table 2. Labels of the variables used for the control system.

	COD/N (V.L)	COD/N (L)	COD/N (N)	COD/N (H)	COD/N (V.H)
$[N\text{-}NH_4^+]_{in}$ (V. L)	0<B<1	0<B<1	0<B<1	0<B<1	0<B<1
	0<R<1	0<R<1	0<R<1	0<R<1	0<R<1
$[N\text{-}NH_4^+]_{in}$ (L)	1<B<3	1<B<3	0<B<1	0<B<1	0<B<1
	3<R<67	3<R<67	3<R<67	3<R<67	3<R<67
$[N\text{-}NH_4^+]_{in}$ (N)	3<B<5	3<B<5	0<B<1	0<B<1	0<B<1
	67<R<135	67<R<135	67<R<135	67<R<135	67<R<135
$[N\text{-}NH_4^+]_{in}$ (H)	5<B<8	5<B<8	3<B<5	0<B<1	0<B<1
	135<R<236	135<R<236	135<R<236	135<R<236	135<R<236
$[N\text{-}NH_4^+]_{in}$ (V. H)	8<B<10	8<B<10	3<B<5	0<B<1	0<B<1
	236<R<370	236<R<370	236<R<370	236<R<370	236<R<370

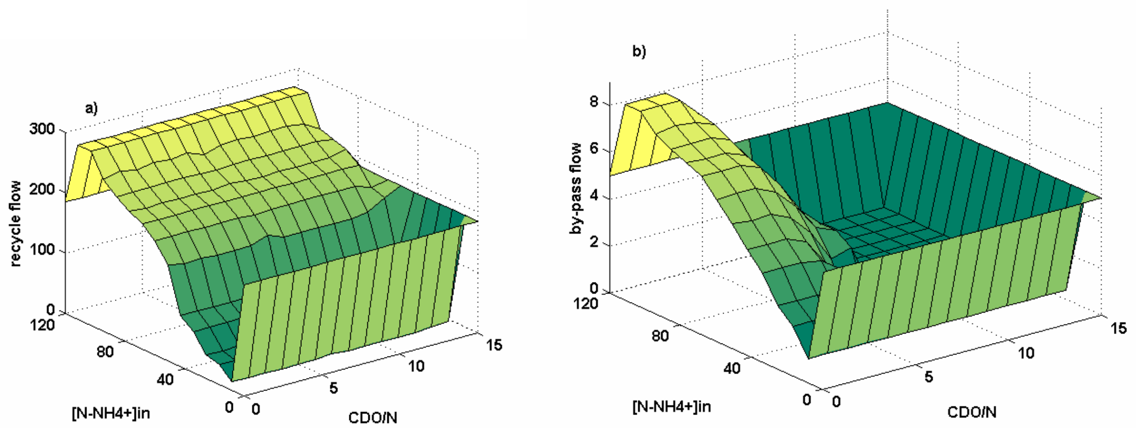

Fig. 2. Surface plot of the fuzzy logic control system: a) output recycle flow (R) and b) by-pass flow (B) versus COD/N ratio and $N\text{-}NH_4^+$ concentration in the effluent.

3. Results and discussion

The supervisory system was tested on the lab-scale biological wastewater treatment process described above. The wastewater is made by mixing two concentrated streams of carbon (acetate) and nitrogen (ammonium chloride) diluted with tap water. Different COD and Nitrogen concentrations and flow rates are automatically assigned and scheduled by the supervisory computer. This artifact enables to simulate real influent situations of organic and hydraulic shocks.

Fig. 3 presents results concerning each reactor operation, when a step increase in nitrogen concentration from 20 to 60 mg N/L (keeping constant the influent COD) was applied at time 0 and kept for 73 hours. During this period the process was intensively monitored every 2 hours. Due to the off-line nature of some analytical techniques the supervisory system received information with a delay. However after 15 hours, the output of the fuzzy system was able to set the proper flow conditions.

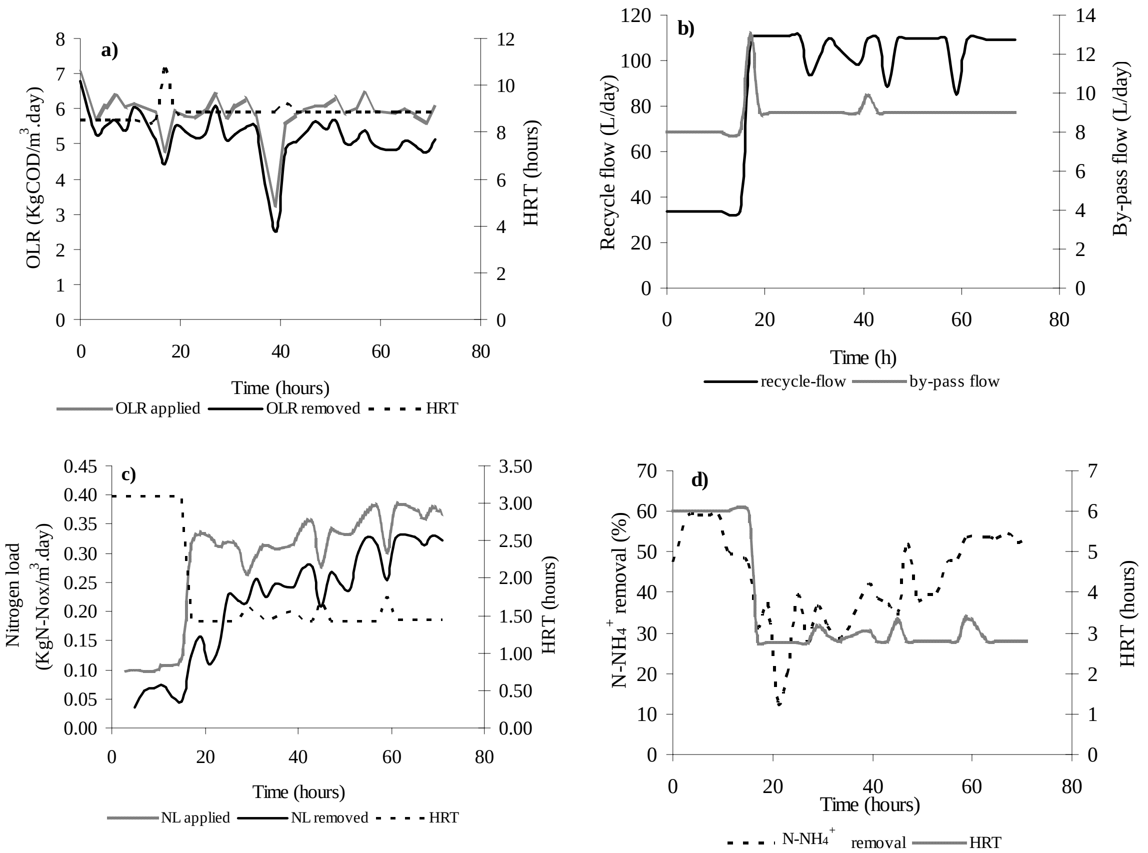

Fig. 3. Time course of main variables during the nitrogen overload.
a) anaerobic reactor; b) anoxic reactor; c) anoxic reactor, and d) nitrification tank.

The fuzzy system automatically increased the recycle flow rate from 34 to 111 L/day and the by-pass flow rate from 8 to 13 L/day (Fig. 3b), in order to remove the surplus nitrate and to maintain the COD/N ratio necessary to remove all nitrogen. In the anaerobic reactor the removed Organic Loading Rate is almost coincident with the applied OLR (Fig. 3a) which corresponds to high COD removal efficiencies ranging from 96 to 85% (data not shown). The HRT ranged from 8.9 h to 10.7 h (Fig. 3a). The fluctuations in the HRT of this module were consequence of the by-pass flow rate adjustments needed to provide enough COD for efficient denitrification in the anoxic module. The by-pass flow rate is therefore directly dependent on the COD removal efficiency of the anaerobic reactor. The decrease on the by-pass flow rate after the first adjustment (Fig. 3b), is due to the decrease in the COD removal efficiency in the anaerobic module. The anoxic reactor achieved a maximum of 89% $N\text{-}NO_x^-$ (nitrate and nitrite) conversion to N_2 gas, at an HRT as low as 1.4 hours (Fig. 3c). The carbon/nitrogen ratio was maintained higher than the theoretical value of 4.7 during the assay and the excess COD that was not used for denitrification was efficiently converted to methane (not shown). The specific methanogenic acetoclastic activity of the granular sludge in this module kept 71% of the inoculum value. The decrease on the hydraulic retention time in the nitrification tank to a value as low as 3 hours did not impair the rise of the ammonia removal efficiency, from 12 to 50% during the trial period (Fig. 3d).

4. Conclusions

A KBES using rule based fuzzy logic was developed and applied to a lab-scale plant comprising anaerobic/anoxic/aerobic modules for combined high rate biological N and C removal. A step increase in ammonia concentration from 20 to 60 mg N/L was applied during a trial period of 73 hours. Recycle flow rate from the aerobic to the anoxic module and by-pass flow rate from the influent directly to the anoxic reactor were the output of the fuzzy system that were automatically changed (from 34 to 111 L/day and from 8 to 13 L/day, respectively), when new plant conditions were recognized by the expert system. Denitrification efficiency higher than 85% was achieved 30 hours after the disturbance and 15 hours after the system response at an HRT as low as 1.5 hours. Nitrification efficiency gradually increased from 12 to 50% at an HRT of 3 hours. The system proved to properly react in order to set adequate operating conditions that timely led to recover efficient N and C removal rates.

References

APHA, AWWA, WPCF (1989). *Standard Methods for the Examination of Water and Wastewater*, 17th edn., Washington D.C.

Baeza J. A., Ferreira E. C. and Lafuente J. (2000). Knowledge-based supervision and control of wastewater treatment plant: a real-time implementation. *Wat. Sci. Tech.*, **41**(12), 129-137.

Baeza J. A., Gabriel D. and Lafuente J. (1999). An expert supervisory system for a pilot WWTP. *Environ. Modelling & Software*, **14**, 383-390.

Barnett M. W., Patry G. G. and Hiraoka M. (1992). Knowledge-based (expert) systems for the activated sludge process. In: *Dynamics and Control of the Activated Sludge Process*, J.F. Andrews (ed.), Technomic Publ. Co., Lancaster, pp. 231-243.

Carrasco E. F., Rodríguez J., Puñal A., Roca E. C. and Lema J. M. (2002). Rule-based diagnosis and supervision of a pilot-scale wastewater treatment plant using fuzzy logic techniques. *Expert Systems with Applications*, **22**, 11-20.

Chapman D., Patry G. G. and Hill R. (1989). Dynamic modeling and expert systems in wastewater engineering: trends, problems, needs. In: *Dynamic Modeling and Expert Systems in Wastewater Engineering*, ch. 11, G. G. Patry and D. Chapman (eds.), Lewis Publ., Chelsea, pp. 345-370.

Du Y. G., Tyagi R. D. and Bhamidimarri R. (1999). Use of fuzzy neural-net model for rule generation of activated sludge process. *Proc. Biochem.*, **35**, 77-83.

Flores J., Arcay B. and Arias J. (2000). An intelligent system for distributed control of an anaerobic wastewater treatment process. *Artificial Intelligence*, **13**, 485-494.

Genovesi A., Harmand J. and Steyer J.-P. (1999). A fuzzy logic based diagnosis system for the online supervision of an anaerobic digester pilot-plant. *Biochem. Eng. J.*, **3**, 171-183.

Meyer U. and Pöpel H. J. (2003). Fuzzy-control for improved nitrogen removal and energy saving in WWWT-plants with pre-denitrification. *Wat. Sci. Technol.*, **47**(11), 69-76.

Müller A., Marsilli-Libelli S., Aivasidis A., Lloyd T., Kroner S. and Wandrey C. (1997). Fuzzy Control of Disturbances in a Wastewater treatment Process. *Wat. Res.*, **31**(12), 3157-3167.

Olsson B. and Newell B. (1999). *Wastewater Treatment Systems – Modelling, Diagnosis and Control*. IWA Publishing, London.

Ozgur N. H. and Stenstrom M. K. (1994). KBES for Process Control of Nitrification in Activated Sludge Process. *J. Environ. Eng.* **120**(1), 87-107.

Patry G. G. and Chapman D. (1989). *Dynamic Modeling and Expert Systems in Wastewater Engineering*. Lewis Publishers, Chelsea.

Polit M., Estaben M. and Labat P. (2002). A fuzzy model for an anaerobic digester, comparison with experimental results. *Artificial Intelligence*, **15**, 385-390.

Puñal A., Rodríguez J., Carrasco E. F., Roca E. and Lema J. M. (2002a). An expert system for monitoring and diagnosis of anaerobic wastewater treatment plants. *Wat. Res.*, **36**, 2656-2666.

Puñal A., Rodríguez J., Carrasco E. F., Roca E. and Lema J. M. (2002b). Expert System for the online diagnosis of anaerobic wastewater treatment plants. *Wat. Sci. Tech.*, **45**(10), 195-200.

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