Energy saving for air supply in a real WWTP: application of a fuzzy logic controller

G. Bertanza IWA, L. Menoni and P. Baroni

ABSTRACT

An unconventional cascade control system, for the regulation of air supply in activated sludge wastewater treatment plants (WWTPs), was tested. The dissolved oxygen (DO) set point in the aeration tank was dynamically calculated based on effluent ammonia concentration, following a fuzzy logic based approach. First, simulations were conducted, according to the BSM2 protocol, for a general comparison with more conventional control strategies. It turned out that the effluent quality could be improved by 7–8%, based on the EQI parameter. Moreover, the aeration energy requirement could be reduced up to 13%. Subsequently, the system was installed in a full-scale WWTP. While stably complying with the ammonia effluent standard (10 mg/L), excess air supply was prevented, and a reduction of the specific power consumption (kWh/kgCOD$_{removed}$) of 40–50% was recorded with respect to the previously installed PID controller (fixed DO set point).

Key words | activated sludge, cascade control, municipal wastewater, nitrification, simulation, smart control strategy

G. Bertanza IWA (corresponding author)
L. Menoni
DICATAM – Department of Civil, Environmental, Architectural Engineering and Mathematics,
Università degli Studi di Brescia,
via Branze 43, 25123, Brescia,
Italy
E-mail: *giorgio.bertanza@unibs.it*

P. Baroni
DII – Department of Information Engineering,
Università degli Studi di Brescia,
via Branze 38, 25123, Brescia,
Italy

INTRODUCTION

In the last few decades, the increase in the cost of supplying energy and the simultaneous introduction of strict environmental standards have made the topic of the energy use in the water sector of great relevance. As a consequence, wastewater treatment plants (WWTPs) are facing the issue of the reduction of energy consumption, i.e. operational costs, as well as the need to improve their effluent quality in order to meet stricter discharge limits.

Energy consumption in WWTPs depends on several factors, such as plant location and size, origin and characteristics of wastewater, flow rate and polluting load into the plant, hydraulic conditions, type of biological process, pumping station, sludge treatment line and energetic efficiency of the equipment. For conventional municipal WWTPs, energy costs are in the range of 5–10% of the total yearly costs, including both construction and operation; 60% of the overall energy consumption in a conventional WWTP is related to biological treatment, mainly the aeration aspects (WEF 2009), followed by the sludge treatment train (about 20%) and the pumping station (about 15%). Some authors report that aeration can account for up to 75% of the total energy usage (Rosso *et al.* 2008).

In order to improve WWTP efficiency and to reduce the cost of treatments, instrumentation control and automation (ICA) were introduced in this sector: the first ICA applications were in the 1970s within the activated sludge process for organic matter removal. Many different kinds of controller were developed and simulated, including rule-based control, fuzzy logic control, linear quadratic control and model predictive control but, in most cases, the full-scale application of control strategies is limited to linear controllers, the most common being the proportional integral (PI) and the proportional integral derivative (PID) controllers (Olsson 2012; Åmand *et al.* 2013).

The air supply in the biological process is, in general, the most commonly controlled parameter due to its crucial role in the operation of WWTPs. The basic level of aeration control consists of keeping a stable dissolved oxygen (DO) concentration, independently from load fluctuations, by manipulating either the air flow rate or the speed/submergence of the mechanical aerators; this is generally achieved by employing PI or PID controllers. The most frequent problems in controlling DO at a constant set point are related to the reduced flexibility associated with influent load fluctuations (Beltrán *et al.* 2015). Activated sludge treatment is a

doi: 10.2166/wst.2020.084

complex and nonlinear process in which time constants vary in a wide range (i.e., the air flow demand varies over a day, week and year as well as along the aeration tank); it is never in a steady-state (Åmand et al. 2013); hence, high control performance, by using linear controllers (such as PID), is rarely achieved if proper tuning is not carried out (see also the 'Results and discussion' section, Figure 2).

As an alternative to linear controllers, unconventional control strategies have been widely studied. In particular, controllers based on fuzzy logic have been discussed since the 1980s (Tong et al. 1980), and have intermittently returned to favour (Serralta et al. 2002; Meyer & Pöpel 2003; Fiter et al. 2005; Traoré et al. 2005; Yong et al. 2006; Han et al. 2008), due to the capability of fuzzy logic to provide an intuitive formal representation of the process, indeed, it is possible to include operator experience and process knowledge in the controller.

Nevertheless, the publications dealing with fuzzy controllers report mainly either simulations or pilot-scale investigations. Simulations are generally related to different plant layouts, influent load characteristics, simulation procedures and effluent legislative requirements. Moreover, the performances of the various controllers are evaluated using non-standardized parameters. All these aspects make the systematic comparison of possible alternative solutions very difficult.

To address this issue, the International Water Association Task Group on Benchmarking of Control Strategies for Wastewater Treatment Plants developed the benchmark simulation model (BSM; Gernaey et al. 2014). In particular, benchmark simulation model No. 2 (BSM2) consists of a standard layout that includes a primary clarifier, five tanks in series for activated sludge (two unaerated tanks followed by three aerated tanks) and a secondary settler for the water line, while the treatment train for the sludge line is composed of a thickener, an anaerobic digester and a dewatering unit. The dynamic influent used for the simulation is generated with a phenomenological model (Gernaey et al. 2011). A standardized simulation protocol (simulation period of 609 days and evaluation period of one year) is defined along with an open-loop configuration and a default closed-loop scenario (to be used as reference scenario for the comparison of different control strategies). Moreover, a set of evaluation criteria is identified in order to ensure objective comparison. A detailed description of BSM2 protocol is reported in Gernaey et al. (2014).

However, even if software modelling can provide almost unlimited flexibility and opportunities in control and process development (which is useful in a preliminary phase), there is a gap between the limitations of real applications and the opportunities that a simulation study can offer. Therefore, the need for full-scale validation of each control strategy is well recognised (Jeppsson 2017). As far as we are aware, the full-scale applications of fuzzy controllers are still scarce in the scientific literature: some results have been reported but they are not related to DO control in a full-scale municipal conventional activated sludge plant.

We patented the 'oxy-fuzzy for water' control system. Results of a prototype application on a full-scale plant were previously published (Baroni et al. 2006). A first aim of this work was to obtain an objective comparison, which had not yet been done with conventional control strategies, through a simulation phase. This was conducted according to the standardized BSM2 protocol. Moreover, to fill the gap of field validation, a version of the controller at a higher technology readiness level (TRL), than the one previously studied was applied to a full-scale WWTP. The evaluation carried out mainly focused on the efficiency of the control system and the energy consumption/cost of treatment.

MATERIALS AND METHODS

The controller studied is composed of two modules: the dissolved oxygen set point (DOSP) module and the air flow rate (AFR) module. The first module (DOSP) receives as inputs the effluent ammonia concentration measured at 15 min intervals (the highest frequency permitted by the on-line measuring device installed at the full-scale plant) and the ammonia variation rate over a period of 30 min (i.e. calculated based on the last 2–3 measured concentrations). By combining these two inputs, it calculates as the output the percentage variation of the DO set point (every 15 min) with respect to the previous DO set point value. The proper DO concentration in the tank is determined in order to ensure that the effluent ammonia concentration remains within a predefined range; thus, the DO set point varies dynamically, taking into account effective process conditions (nitrification rate and influent load variability).

The second module (AFR) regulates airflow (by calculating the percentage variation of the valve position every minute), to guarantee a DO concentration in the oxidation tank as close as possible to the calculated set point. It therefore receives as inputs the oxygen concentration measured each second and calculates: (a) the average over one minute, (b) the percentage error between the desired and measured DO value, and (c) the variation rate over a period of 12 min. The operation of the controller is described in detail in Baroni *et al.* (2006).

Before implementing the innovative controller based on fuzzy logic at full scale, simulations were carried out in the framework of BSM2 in order to obtain an objective comparison with a conventional air supply controller. The free code made available in Matlab/Simulink by Gernaey *et al.* (2014) was used.

The following control strategies for air supply were simulated:

- Open-loop BSM2 configuration (OL), i.e. constant aeration with the following fixed default K_La coefficients in the aerobic tanks: 120 d^{-1}, 120 d^{-1} and 60 d^{-1} (Gernaey *et al.* 2014).
- Default closed-loop BSM2 configuration (CL0): a fixed DO set point of 2 mg/L is kept in the intermediate aerated tank (#4), by manipulating K_La_4 with a PI controller. For the other reactors, the same ratios as in the previous scenario were used: $K_La_3 = K_La_4 = 2\ K_La_5$ (Gernaey *et al.* 2014).
- Adapted version of the oxy-fuzzy controller (F): a variable DO set point in the third aerated tank (where the effluent ammonia concentration should be measured in a full-scale application) is calculated by the DOSP fuzzy module of the patented controller. The DO concentration is then adjusted by manipulating K_La_5 with a traditional PI controller. Air supply in the other reactors is varied by calculating the corresponding K_La values, using the same ratios as in the previous scenarios. It was not possible to use the AFR module of the complete fuzzy logic controller for adjusting the air flow, because the simulation software does not include tools for describing the physical behaviour of mechanical devices of the air supply system (such as blowers and valves).

The evaluation criteria of the BSM2 protocol were considered (Gernaey *et al.* 2014):

- Effluent quality index (EQI) as the weighted average sum of the following effluent concentrations: total suspended solids (TSS), chemical oxygen demand (COD), total Kjeldahl nitrogen (TKN), nitrates and nitrites (NO), biochemical oxygen demand (BOD).
- Duration of total nitrogen (18 mg/L) and ammonia nitrogen (4 mg/L) effluent limit violation.
- Operational cost index (OCI) as the weighted sum of the costs for aeration energy (AE), pumping energy, sludge production for disposal, external carbon addition, mixing energy, methane production and heating energy.

The WWTP chosen for full-scale implementation is a conventional activated sludge plant (design size 350,000 people equivalent; p.e.) with the biological treatment divided into three parallel lines. In this plant, the aeration supply accounts for 55% of the total energy demand, thus energy saving in this section is an important issue. The traditional DO control strategy is based on the measurement of the DO concentration in the tanks, to be compared with a fixed DO set point, without taking into consideration effective nitrification process performance and the influent load variability. To overcome the limitations of this type of control strategy, the fuzzy-based system was installed in two of the three biological treatment lines (total volume = 25,000 m^3). The air supply system consists of two centrifuge blowers (20,000 Nm^3/h) and fine bubbles diffusers. The plant is not located in a sensitive area, so the standard for effluent NH_4^+ concentration is 15 mg/L.

The following are the main components of the oxy-fuzzy system for each one of the two lines (the design criteria were the same for both): an N-NH_4^+ on-line probe for effluent ammonia concentration monitoring, two oximeters placed in the intermediate and outlet sections of the biological reactor, a system for data acquisition and elaboration, the fuzzy controller, an output control decision actuation system that opens/closes the valve to regulate the air flow. A detailed description of the apparatus that makes up the entire control system is reported in Baroni *et al.* 2006.

The first step of the full-scale application consisted of a tuning phase of the patented fuzzy controller. Starting with the original version, through a trial and error process based on qualitative observation of experimental data, modifications were adopted in terms of rule definition, membership function shaping and timing of the control actions. This process was very important in terms of adapting the system to the case specific characteristics. Moreover it took several weeks, during which we also to assessed its behaviour under different conditions.

The full-scale performance of the oxy-fuzzy controller was evaluated by comparing the power consumption for aeration measured over two consecutive months (December and January) for two years in a row, the first one using the fixed DO set point controller and the second one the oxy-fuzzy controller. The power consumption was normalized over the influent or removed organic load and flow rate.

Several practical issues were tackled for the application at the full scale: the choice of the representative sections for where to place the OD and ammonia measuring sensors, depending on the hydrodynamic behaviour of reactors; efforts for keeping the sensors efficient by proper maintenance; the need to consider the inertia of mechanical devices (blowers and valves in particular) in the control chain; the presence of limitations of the blowers' capacity (both minimum and maximum air flowrate); the necessity to manage critical events (such as power supply interruption, PC or software default, unreliable electric signals due to different kinds of problems with the measuring devices, etc.); setting a minimum acceptable DO concentration in the aeration tanks to prevent the occurrence of unwanted effects, such as, for instance, the deterioration of the sludge settling properties and the increase of N_2O emissions. This last aspect has been widely studied in recent years (Boiocchi *et al.* 2017; Mannina *et al.* 2019), but was not specifically investigated in the present work.

RESULTS AND DISCUSSION

In the simulated open-loop configuration, total nitrogen and ammonia nitrogen effluent limits (18 mg/L and 4 mg/L) were exceeded for a period of 0.4 day and 30 days, with a 95th percentile of 15.1 mg/L and 4.7 mg/L, respectively. Dissolved oxygen concentration in the three aerated tanks varied over a wide range (0.3–5 mg/L).

With the implementation of the default closed-loop configuration, total nitrogen and ammonia nitrogen effluent limits were exceeded for a period of 4.3 days and 1.5 days, with a 95th percentile of 16.8 mg/L and 1.5 mg/L, respectively. The CL0 configuration improved the performance of the plant in terms of ammonia nitrogen with respect to the OL scenario. The controlled variable (dissolved oxygen concentration in the second aerated tank) was close to the set point, with slight oscillations.

The simulation of the fuzzy controller showed the following results in terms of effluent limits violations: total nitrogen and ammonia nitrogen limits were exceeded for a period of 1.43 days and 3.03 days, with a 95th percentile of 14.83 mg/L and 2.69 mg/L, respectively. The dissolved oxygen concentration in the third aerated tank was close to the set point and oscillations were further reduced. As expected, there was a strong link between DO concentration in the tank and effluent ammonia nitrogen.

The simulated scenarios presented similar performances in terms of the way that BOD_5, COD and TSS effluent limits exceedances.

Table 1 | Evaluation criteria of the different simulated scenarios: comparison between open loop configuration (OL), default closed-loop configuration (CL0) and fuzzy controller (F)

	EQI [kg/d]	OCI [kWh/d]	AE [kWh/d]
OL	5,661	9,208	4,000
CL0	5,577	9,450	4,225
F	5,186	8,892	3,673

Table 1 shows the results of the three simulated configurations in terms of effluent quality (EQI) and costs (OCI). The cost for aeration energy is specified, being the main item influenced by the implementation of different air supply controllers. The plant performance in terms of effluent quality was improved by the introduction of the fuzzy controller by 7–8%. Moreover, the application of the fuzzy controller allowed a reduction of the operating costs of 3.4% and 6% with respect to OL and CL0, respectively. Considering the contribution of the aeration energy, the fuzzy controller reduces the energy consumption in the range of 8–13%.

It may be noted that the results obtained with the fuzzy system (scenario F) are comparable to those obtainable with a similar cascade control strategy, using PID controllers (some tests were conducted during the present study; data not shown). Nevertheless, the fuzzy approach was user friendly and the controller more efficient in stably regulating the plant working conditions, as shown by the real-scale application described below.

In the full-scale plant, the controller performance was assessed both in terms of effect on process parameters (efficiency and stability) and energy consumption, with respect to the original configuration.

Figure 1 shows the typical variations of the controlled parameters (DO set point, valve set point, valve position and air flow) over one day. Data refer, as an example, to one of the tanks equipped with the fuzzy controller. In fact, both of the tanks showed similar behaviour (data not shown). The graph shows that ammonia concentration is stably below the adopted reference safety value of 10 mg/L (the effluent standard being 15 mgNH_4^+/L), and stayed in the range 3–6 mg/L. DO and valve position set points were continuously modified according to the ammonia concentration trend, and the variations of these parameters clearly affected the nitrification efficiency. Excess aeration, typical of fixed DO set point systems, was avoided by reducing the DO set point when ammonia tended to decrease. Furthermore, the DO concentration and the valve position were always close to their set point, thus exhibiting a high control efficiency.

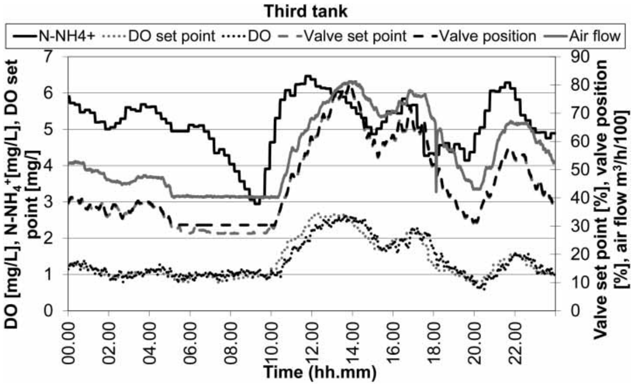

Figure 1 | Typical behaviour of the fuzzy controller installed on the full-scale plant. Trends, over one day, of dissolved oxygen (DO) concentration and set point, N-NH_4^+ concentration, valve position (actual and set point), and air flow.

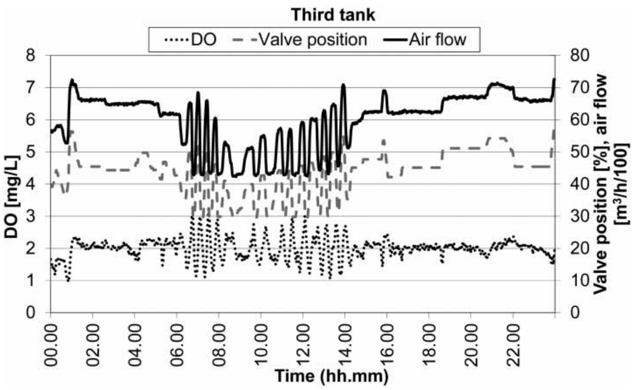

Figure 2 | Example of DO concentration, valve position and air flow trends, with fixed DO set point (2 mg/L; PID controller), in the full-scale plant.

Moreover, overall process stabilization was achieved, reducing both the amplitude and frequency of fluctuation of the controlled parameters, with respect to the previous situation. An example of oscillation problems observed with fixed DO set point (PID controller) is shown in Figure 2.

The energy consumption for air supply was reduced by 22–30%, after the installation of the fuzzy controller. This advantage is even clearer if the specific energy consumption is calculated (see Table 2). Obtained values vary from 27% to 49%. Based on these results, the estimated payback period for the whole control system is less than two years. The total installation costs (including probes, hardware, software licenses, personnel) was estimated to be 150,000 €. Assuming a conservative energy saving of 20% and a daily consumption of 12,000 kWh/d, the yearly saving may be calculated, using the figure of 0.12 €/kWh for the energy cost, as follows:

$$0.2\times 12,000\,\mathrm{kWh/d}\times 0.12€/\mathrm{kWh}\times 350\,\mathrm{d/y} = 100,800€/\mathrm{y}$$

Table 2 | Energy consumption for air supply: comparison between traditional and fuzzy controller over two consecutive months for two years in a row

	Traditional controller	Fuzzy controller
COD_{in} [kg/d]	23,025 23,737	29,953 27,328
$COD_{removed}$ [kg/d]	20,604 20,304	28,070 25,818
Treated flow rate [m^3/d]	75,315 79,572	97,130 83,278
Energy consumption [kWh/d]	12,589 11,705	8,785 9,159
Specific energy consumption [kWh/(p.e. × y)]$^{(*)}$	22 20	12 13
Specific energy consumption [kWh/m^3]	0.17 0.15	0.09 0.11
Specific energy consumption [kWh/kg$COD_{removed}$]	0.61 0.58	0.31 0.35

Average COD mass loadings over the observation period are shown. Daily measurements were carried out (flowrate volume and COD analysis on 24 hour composite samples).
$^{(*)}$assumed daily per-capita COD production = 110 g/(p.e.*d).

CONCLUSIONS

In this work, the application of an unconventional fuzzy logic cascade controller for the air supply system was tested both at simulation scale and at full scale. Indeed, even if, over the last decades, original controllers have been widely studied at simulation scale, real applications are rarely reported in the scientific literature.

The oxy-fuzzy controller implemented at full scale confirmed the preliminary results obtained at simulation scale. It showed good control performance, ensuring the required amount of ammonia removal. Moreover, an improvement of process stability and a promising energy saving were obtained with respect to the traditional fixed DO controller. Simultaneously, a short payback time (less than two years) was estimated for the investment.

ACKNOWLEDGEMENTS

This work was partially funded by the Italian Ministry for University and Research, within the Smart Cities and Communities and Social Innovation programme, Project SWaRM-Net-Smart Water Resource Management – Networks' (SCN_00198).

REFERENCES

Åmand, L., Olsson, G. & Carlsson, B. 2013 Aeration control – a review. *Water Sci. Technol.* **67** (11), 2374–2398.

Baroni, P., Bertanza, G., Collivignarelli, C. & Zambarda, V. 2006 Process improvement and energy saving in a full scale wastewater treatment plant: air supply regulation by a fuzzy logic system. *Environ. Technol.* **27** (7), 733–746.

Beltrán, S., Irizar, I. & Ayesa, E. 2015 Instrumentation, monitoring and real-time control strategies for efficient sewage treatment plant operation. In: *Sewage Treatment Plants: Economic Evaluation of Innovative Technologies for Energy Efficiency* (K. Katerina Stamatelatou & K. P. Tsagarakis, eds). IWA Publishing, London. https://www.iwapublishing.com/books/9781780405018/sewage-treatment-plants-economic-evaluation-innovative-technologies-energy.

Boiocchi, R., Gernaey, K. V. & Sin, G. 2017 A novel fuzzy-logic control strategy minimizing N_2O emissions. *Water Res.* **123**, 479–494.

Fiter, M., Güell, D., Comas, J., Colprim, J., Poch, M. & Rodriguez-Roda, I. 2005 Energy saving in a wastewater treatment process: an application of fuzzy logic control. *Environ. Technol.* **26** (11), 1263–1270.

Gernaey, K. V., Flores-Alsina, X., Rosen, C., Benedetti, L. & Jeppsson, U. 2011 Dynamic influent pollutant disturbance scenario generation using a phenomenological modelling approach. *Environ. Model. Softw.* **26** (11), 1255–1267.

Gernaey, K. V., Jeppsson, U., Vanrolleghem, P. A. & Copp, J. B. 2014 *Benchmarking of Control Strategies for Wastewater Treatment Plants*. IWA Publishing, London, UK.

Han, Y., Brdys, M. & Piotrowski, R. 2008 Nonlinear PI control for dissolved oxygen tracking at wastewater treatment plant. *World Congr.* **17** (1), 13587–13592.

Jeppsson, U. 2017 The Benchmark Simulation Modelling Platform–Areas of Recent Development and Extension. In: *Frontiers International Conference on Wastewater Treatment and Modelling*. Springer, Cham, pp. 81–91.

Mannina, G., Rebouças, T. F., Cosenza, A. & Chandran, K. 2019 A plant-wide wastewater treatment plant model for carbon and energy footprint: model application and scenario analysis. *J. Cleaner Prod.* **217**, 244–256.

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

Olsson, G. 2012 ICA and me – a subjective review. *Water Res.* **46** (6), 1585–1624.

Rosso, D., Stenstrom, M. & Larson, L. 2008 Aeration of large-scale municipal wastewater treatment plants: state of the art. *Water Sci. Technol.* **57** (7), 973–978.

Serralta, J., Ribes, J., Seco, A. & Ferrer, J. 2002 A supervisory control system for optimising nitrogen removal and aeration energy consumption in wastewater treatment plants. *Water Sci. Technol.* **45** (4–5), 309–316.

Tong, R. M., Beck, M. B. & Latten, A. 1980 Fuzzy control of the activated sludge wastewater treatment process. *Automatica* **16** (6), 695–701.

Traoré, A., Grieu, S., Puig, S., Corominas, L., Thiery, F., Polit, M. & Colprim, J. 2005 Fuzzy control of dissolved oxygen in a sequencing batch reactor pilot plant. *Chem. Eng. J.* **111** (1), 13–19.

WEF 2009 *Energy Conservation in Wastewater Treatment Facilities – Manual of Practice – No. 32*. Water Environment Federation, Alexandria, VA, USA.

Yong, M. A., Yong-Zhen, P., Xiao-Lian, W. & Shu-Ying, W. 2006 Intelligent control aeration and external carbon addition for improving nitrogen removal. *Environ. Modell. Softw.* **21** (6), 821–828.

First received 3 October 2019; accepted in revised form 18 February 2020. Available online 25 February 2020