Technical University of Denmark



Control of wastewater N2O emissions by balancing the microbial communities using a fuzzy-logic approach

Boiocchi, Riccardo; Gernaey, Krist V.; Sin, Gürkan

Published in: IFAC-PapersOnLine

Link to article, DOI: 10.1016/j.ifacol.2016.07.359

Publication date: 2016

Document Version Publisher's PDF, also known as Version of record

Link back to DTU Orbit

Citation (APA):

Boiocchi, R., Gernaey, K., & Sin, G. (2016). Control of wastewater N2O emissions by balancing the microbial communities using a fuzzy-logic approach. In IFAC-PapersOnLine (Vol. 49, pp. 1157-1162). Elsevier Science. (IFAC Proceedings Volumes (IFAC-PapersOnline)). DOI: 10.1016/j.ifacol.2016.07.359

DTU Library Technical Information Center of Denmark

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Available online at www.sciencedirect.com



IFAC-PapersOnLine 49-7 (2016) 1157-1162



Control of wastewater N₂O emissions by balancing the microbial communities using a fuzzy-logic approach

Riccardo Boiocchi*. Krist V. Gernaey*. Gürkan Sin*

*Dept. of Chemical and Biochemical Engineering, Technical University of Denmark, Kgs. Lyngby, 2800 Denmark (Tel: +4545252806; e-mails: <u>ricca@kt.dtu.dk</u>, <u>kvg@kt.dtu.dk</u>, <u>gsi@kt.dtu.dk</u>).

Abstract: In this work, a fuzzy-logic controller for minimization of the nitrous oxide emission from wastewater treatment plants is developed and tested in a simulation environment. The controller is designed in order to maintain a balance between production and consumption of nitrite by AOB and NOB microorganisms respectively. Thus, accumulation of nitrite is prevented and AOB denitrification, the main N₂O producer, is drastically slowed down. The controller is designed to adjust the oxygen supply according to a measured parameter which typically indicates the ratio of the activity of NOB over AOB. The controller is tested on a benchmark simulation model describing the production of N₂O during both AOB denitrification and HB denitrification. Comparisons between simulation results of open-loop and closed-loop have revealed the potential of the controller to significantly reduce the amount of N₂O emitted (approximately 35%). On the other side, this reduction of N₂O was accompanied by an increase in the aeration costs. Moreover, a plant performance evaluation under dynamic disturbances shows that the effluent quality is compromised due to higher requirements of organic carbon by denitrifying heterotrophs. The controller can therefore be considered effective for the reduction of N₂O production by AOB but would need to be coupled with a secondary control strategy ensuring a complete oxidation of the nitrogen oxides by heterotrophs to have a good effluent quality.

© 2016, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved.

Keywords: fuzzy-logic, benchmark, nitrous oxide emission, autotrophic denitrification, nitrogen, wastewater treatment plants (WWTPs).

1. INTRODUCTION

Nitrous oxide (N₂O) is well-known as an ozone-depleting substance and a harmful greenhouse gas with a global warming potential 300 times higher than carbon dioxide. Measurement campaigns at wastewater treatment plants (WWTPs) have revealed that a considerable amount of N₂O can be emitted [1,2]. Developing control strategies aiming at reducing its emissions becomes therefore of interest. During the biological WWT processes, N₂O is found to be produced by two different microbial groups: ammonia-oxidizing bacteria (AOB) and heterotrophic bacteria (HB) [3]. In particular, AOB have shown their capability in using the produced NO₂⁻ instead of O₂ as electron acceptor for the oxidation of NH₄⁺. The reduction of NO₂⁻ carries N₂O as end product. Another possible pathway is the incomplete hydroxylamine oxidation by AOB. Intermediate compounds accumulated during this process can lead to N₂O. With regard to the role of HB, N₂O is produced as intermediate compound during the reduction of nitrogen oxides like NO3⁻ and/or NO2⁻ into N₂. If the reduction of N₂O into N₂ is slower than the reduction of those N oxides into N₂O, an accumulation of N₂O can occur. The minimization of N₂O emissions can therefore be achieved by slowing down both the AOBmediated N₂O-production processes and the net HB-mediated N₂O production. Furthermore, operational costs have to be

taken into account in order to evaluate the economic feasibility of the control implementation.

For the development of a control strategy applied to biological wastewater processes, a fuzzy-logic approach can be the most suitable to be adopted. As a matter of fact, given their interactive nature and their high non-linearity, biological wastewater treatments can be more suitably controlled by fuzzy-logic controllers than by linear controllers like the Proportional Integrative Derivative (PID) ones [4]. Furthermore, fuzzy-logic controllers (FLCs) present the additional possibility of incorporating expert knowledge about the processes to be controlled [5]. FLCs are also not affected by the capability of a mathematical model in describing realistically the processes to be controlled, since their design is independent from the model used. Furthermore, adopting a fuzzy-logic approach easily allows including the fuzziness associated with the control objectives, typically related to the WWT processes [6]. For these reasons, a FLC aiming at minimizing the N₂O emissions by balancing the activity of the different microbial groups is developed the present work. In in particular, MATLAB/Simulink is used as computer environment for the development of the fuzzy-logic control strategy. The model employed for testing its performance is the Benchmark Simulation Model N°2 for Nitrous oxide (BSM2N), developed by Boiocchi et al. [7]. On this platform, dynamic simulations will be performed in order to evaluate the

2405-8963 $\[mu]$ 2016, IFAC (International Federation of Automatic Control) Hosting by Elsevier Ltd. All rights reserved. Peer review under responsibility of International Federation of Automatic Control.

capability of the controller in reducing the N_2O emissions and its contextual effect on effluent quality and operational costs.

2. MATERIALS AND METHODS

2.1 The Benchmark Simulation Model nº2 for Nitrous oxide

As mentioned in the introduction, the model on which the performance of the controller is tested is the Benchmark Simulation Model N°2 for Nitrous oxide (BSM2N), developed by Boiocchi et al. [7]. The model is an extension of the Benchmark Simulation Model N°2 (BSM2) by Jeppsson *et al.* [8]. It describes the physical and biochemical mainstream and side-stream processes occurring in a typical pre-denitrification WWTP. The virtual configuration of the BSM2N is presented in Figure 1. As can be seen, the biological mainstream unit consists of two well-mixed anoxic tanks (ANOX1 and ANOX2) followed by three aerated tanks (AER1, AER2 and AER3). The biological processes occurring in these reactors are described by an upgraded version of the Activated Sludge Model Nº1 (ASM1) by Henze et al. [9], namely the Activated Sludge Model for Greenhouse gases Nº1 (ASMG1) by Guo and Vanrolleghem [10]. The state variables of the ASMG1 are: oxygen (S_{02}) ; readily-biodegradable and slowly-biodegradable carbon (S₈ and X_s); ammonium, nitrite, nitrate, dinitrogen, nitric and nitrous oxide nitrogen (S_{NHx}, S_{NO2}, S_{NO3}, S_{N2}, S_{NO} and S_{N2O}); soluble and particulate inerts $(S_I \text{ and } X_I)$; soluble and particulate organic nitrogen (S_{ND} and X_{ND}); alkalinity (S_{ALK}); heterotrophic, ammonia-oxidizing and nitrite-oxidizing bacteria (X_{HB} , X_{AOB} and X_{NOB}). The processes included in the ASMG1 are: aerobic growth of X_{HB}; hydrolysis of X_S, hydrolysis of X_{ND}; ammonification of S_{ND}; aerobic growth of X_{AOB} ; aerobic growth of X_{NOB} ; anoxic growth of X_{HB} on S_{NO3} , on S_{NO2} , on S_{NO} and on S_{N2O} ; anoxic growth of X_{AOB} on S_{NO2} and on S_{NO} ; decay of X_{HB} , X_{AOB} and X_{NOB} . As can be noted, N₂O is modelled to be produced according to two pathways: during HB denitrification and during nitrite reduction (via nitric oxide) by AOB. On the other hand, the production of N₂O as a consequence of incomplete hydroxylamine (NH₂OH) oxidation by AOB is not included in the model. There is however a significant amount of fullscale experiences suggesting AOB denitrification instead of the incomplete NH₂OH oxidation as the main contributor of N₂O [1,11–15]. Furthermore, a recently-developed model including the incomplete NH₂OH reveals that the amount of N₂O possibly produced during this process would be rather low compared to the amount of N₂O produced during AOB and HB denitrification [16].



Figure 1: BSM2N layout [8].

2.2 Fuzzy-logic inference system

In this section, a brief overview of the work of a fuzzy-logic inference system is presented in order to allow a better understanding of the typical features needed to be decided when designing a fuzzy-logic controller. A fuzzy-logic inference system consists of the following three main sequential operations:

- 1) Fuzzification, where numerical (crisp) inputs are converted into linguistic (fuzzy) inputs, according to predefined membership functions (MFs),
- Fuzzy inference, where fuzzy outputs are deduced on the basis of the fuzzy inputs deduced in point 1), according to specified linguistic rules,
- Defuzzification, where fuzzy outputs are converted into numerical (crisp) outputs according to predefined MFs and a chosen defuzzification method.

As can be deduced, the main parameters to be decided during the design of a fuzzy-logic controller are the MFs of input and output variables and the linguistic rules linking input to output variables. Further details about the generic work of a fuzzy-logic inference system are given in Lababidi and Baker [17].

2.3 Definition of control structure

As mentioned in the introduction, the controller has to be designed in such a way that it minimizes the production of N_2O by both AOB and HB. Heterotrophic denitrification can only occur under low oxygen conditions. The process can therefore occur in the anoxic zone (ANOX1 and ANOX2) and at very poor oxygenation regimes in the aerobic zone (AER1, AER2 and AER3). The contribution on N_2O by HB however would be stronger in the aerobic zone due to the higher mass transfer capability. In the anoxic zone, the HB-produced N_2O stays in the liquid phase and thus is more likely to be reduced into N_2 rather than to strip.

With regard to the production of N_2O during AOB denitrification, it is well-established that low oxygen concentrations and/or high nitrite (NO_2^-) availability promote the use of NO_2^- itself by AOB as electron acceptor for the oxidation of ammonium (NH_4^+). Hence, for its minimization, in the aerobic zone the oxygen has to be in a sufficiently high concentration to enhance the consumption of the AOB-

produced NO₂⁻ by the coexisting microbial group, namely NOB. Enhancing the NOB activity by means of oxygen supply increase would contextually minimize the amount of N₂O produced by HB [18]. Thus the control of R_{NatAmm} can result beneficial for the reduction of the N₂O produced by both AOB and by HB.

For these reasons, monitoring the NOB activity over the one of AOB has been identified as a potential strategy for the minimization of the production of N_2O . The variable identified to be controlled at this purpose is the ratio between the nitrate produced by NOB and the ammonium consumed by AOB (R_{NatAmm}) in the aerobic zone, expressed in Eqn. (1).

$$R_{\text{NatAmm}} = \frac{|(NO_3^-)_{\text{IN}} - (NO_3^-)_{\text{OUT}}|}{|(NH_4^+)_{\text{IN}} - (NH_4^+)_{\text{OUT}}|}$$
(1)

A value of R_{NatAmm} around 1 theoretically indicates that all the nitrite produced by AOB is subsequently consumed by NOB. If R_{NatAmm} is lower than 1, not all the AOB-produced NO₂⁻ is consumed by NOB. Thus NO₂⁻ starts accumulating in the system, which would in turn enhance AOB denitrification. This is a typical situation resulting from low oxygen availability. On the other side, values of the parameter significantly higher than 1 represent oxygen inhibition of heterotrophic denitrification, where an accumulation of HB-produced NO₂⁻ occurs. A too high oxygen supply would in part directly inhibit the HB-produced NO₂⁻ reduction and consume a larger amount of organic carbon needed by HB. In this scenario, the oxygen supply needs to be turned down to avoid that the accumulated NO₂⁻ to be reduced into N₂O.

In virtue of these considerations, the control strategy use measurements from the influent and effluent of the aerobic zone of NH_4^+ and NO_3^- for the calculation of R_{NatAmm} , namely the controlled variable. The oxygen mass transfer coefficient (k_La) is used as a manipulated variable since changes in the oxygen availability forms the only available actuator that is able to induce the due shift on NOB activity. The fuzzy-logic controller is implemented in the mainstream aerobic zone as depicted in Figure 2. As can be seen, the controller will use R_{NatAmm} as direct input variable and will deduce a scaled deviation of the oxygen mass transfer coefficient ($\Delta_{\rm S} k_{\rm L} a$) as output variable. The latter will have a value between -1 and +1. $\Delta_{S}k_{L}a$ is then multiplied by a scaling factor (SF_{kLa}) in order to obtain its physical dimension. The deviations of k_La are integrated in time and then added up to their respective nominal values.



Figure 2: Block diagram for the implementation of the controller in the mainstream activated sludge unit.

2.4 Control tuning

The membership functions for the input and output variables are defined as represented in Figure 3 while Table 1 shows the linguistic rules to enable deducing, on the basis of the values of R_{NatAmm} , the variation of the k_La to be actuated on the three aerobic tanks. R_{NatAmm} is considered to be "GOOD" when it is comprised within 0.99 and 1.2. The reason for allowing a value of R_{NatAmm} slightly higher than 1 is due to the fact that a fraction of the incoming organic nitrogen, after being hydrolysed and ammonified, is usually oxidized into NO₂⁻ and then NO₃⁻. An amount of NO₃⁻ higher than the $NH_4^{\,+}$ (i.e. $R_{NatAmm}{>}1)$ consumed would therefore result. When R_{NatAmm} is in this range, no changes of k_La are designed to be actuated. On the contrary, the maximal positive change of k₁a (i.e. $\Delta_{sk_1}a=+1$) is decided to occur when R_{NatAmm} is equal or below 0.95, a scenario which would indicate that NOB need more oxygen for the conversion of NO_2^- into NO_3^- .When R_{NatAmm} is equal or higher than 1.4, inhibition of heterotrophic denitrification is considered to occur. In this case, the maximal negative change of $k_L a$ (i.e. $\Delta_S k_L a=-1$) is defined to be inferred by the control system.



Figure 3: Membership functions for: (a) R_{NatAmm} , and (b) $\Delta_{S}k_{L}a$.

	IF	THEN
	R _{NatAmm}	$\Delta_{\rm S} k_{\rm L} a$
1	LOW	POSITIVE
2	GOOD	ZERO
3	HIGH	NEGATIVE

 Table 1: linguistic rules.

A value for the $k_{L}a_{NOM}$ equal to 120 d⁻¹ is assigned for the first two aerobic reactors (AER1 and AER2) and a value of 60 d⁻¹ was used for last tank (AER3), as prescribed by Jeppsson *et al.* [8]. 240 d⁻¹, namely the difference between the saturation limit of $k_{L}a$ (i.e. 360 d⁻¹) and the nominal value in the first two tanks (120 d⁻¹) is used as value for the scaling factor.

3. RESULTS

Simulations of the BSM2N open-loop and closed-loop are performed with the aim of addressing the changes due to the implementation of the novel control strategy. In particular, the BSM2N was simulated with a 609-day long dynamic influent by Jeppsson *et al.* [8], whose design details can be found in Gernaey *et al.* [19]. The dynamics and the steady-state of the influent Total Kjeldahl Nitrogen (TKN) load for the last month are depicted in Figure 4.



Figure 4: Dynamics and steady-state of influent TKN.

Corresponding to the same period of time, Figure 5 shows the dynamic results for both open-loop and closed-loop configurations of: (a) N_2O emission factor, calculated as percentage of N_2O emitted per unit of TKN in the influent, (b) R_{NatAmm} , (c) oxygen mass transfer coefficient of the first aerobic tank (AER1), and (d) the oxygen-to-nitrogen loading ratio (RO), calculated according to Eqn. (2) as the ratio between the oxygen supplied into the three aerobic tanks and the TKN in the influent of the first anoxic tank. The present quantity indicates the typical aeration regime of the plant.

$$RO = \frac{\sum_{i=1}^{3} V_i \cdot k_L a_i \cdot (S_{O,SAT} - S_{O,i})}{(S_{NH4,IN} + S_{ND,IN} + X_{ND,IN}) \cdot Q_{IN}}$$
(2)



Figure 5: Last-month dynamics for: (a) N_2O emission factor, (b) R_{NatAmm} , (c) kLa of AER1, and (d) oxygen-to-nitrogen loading ratio.

Next, following the BSM2 protocol for the benchmarking of control strategies, from both the open-loop and closed-loop

simulation results of the last 52 weeks, which allows a comparison more unbiased with regard to plant initial conditions and nominal value of k_La , the following average values are found:

- N₂O emission factors (N₂O_{ef}),
- total nitrogen removal efficiency (η_{TN}),
- R_{NatAmm},
- NO₂⁻ and NO₃⁻ effluent loads,
- Effluent limit violations in percentages of operating time for ammonium and total nitrogen (V_{NH4} and V_{TN} , respectively),
- Effluent Quality Index (EQI), calculated according to Jeppsson *et al.* [8] by taking into account the amount of the different pollutants in the effluent. The higher EQI is, the worst the effluent quality is,
- the average aeration energy (AAE), proportional to the oxygen mass transfer coefficients.

An overall evaluation of the impact of the controller implementation on the plant performance can thus be achieved. Table 2 summarizes the results.

Table 2: Open-loop	and closed-loop	plant performance
	evaluation.	

	units	OPEN LOOP	CLOSED LOOP
N ₂ O _{ef}	$[\% g N_2 O\text{-}N_{EM}.g\text{-}^1 TKN\text{-}N_{IN}]$	0.4	0.26
R _{NatAmm}	[g NO ₃ ⁻ -N.g ⁻¹ NH ₄ ⁺ -N]	0.94	1.15
RO	[g DO _{IN,AS} .g ⁻¹ TKN _{IN,AS}]	4.7	5.3
(NO ₂ ⁻) _{eff}	$[kg NO_2^N.d^{-1}]$	2.3	0.36
(NO ₃ ⁻) _{eff}	$[kg NO_3^ N.d^{-1}]$	167.6	269.1
η_{TN}	$[\% \text{ g TN}_{\text{REM}} \text{.} \text{g}^{\text{-1}} \text{ TN}_{\text{IN}}]$	70.8	60.7
V _{NH4}	[% of operating time]	7.9	2.1
V _{TN}	[% of operating time]	2.2	12.8
EQI	[kg poll.units.d ⁻¹]	5386.8	5650.3
AAE	$[kWh.d^{-1}]$	4026.7	5242

As can be noted, the controller is able to reduce the average N_2O emitted by 35% by keeping the controlled variable, namely R_{NatAmm} , at a higher value. Thus NOB activity is enhanced and, consequently, a higher consumption of NO_2^- results, leading to lower NO_2^- load in the effluent. However, due to the higher NOB activity, the load of NO_3^- in the effluent is drastically increased, which explains in turn the reduced TN removal efficiency (from 70.8% to 60.7%). The effluent quality index is therefore increased accordingly. Also the percentage of operating time in which TN violations (V_{TN}) are recorded is higher for the closed-loop configuration, although the percentage of operating time in which NH_4^+ violations (V_{NH}) occur is reduced due to the

higher AOB resulting from the higher aeration. Since the controller has enhanced the NOB activity by increasing the amount of oxygen supplied, the average aeration costs have increased by approximately 30% compared to the open-loop case.

4. DISCUSSION

The results presented have shown the capability of the controller in reducing significantly the average amount of N₂O emitted by speeding up the NOB activity, which prevents the AOB-produced NO₂⁻ from being reduced to N₂O and . The results suggest that reduction in the total N2O emitted, which can be considered satisfactory, can be improved by further enhancing NOB activity. On the other hand, enhancing the NOB activity meant also to decrease the effluent quality. As a matter of fact, when the AOB-produced NO₂⁻ was not subsequently oxidized into NO₃⁻, heterotrophic denitrification worked more on NO2 and a lower amount of organic carbon was therefore needed compared to the case when the heterotrophic denitrification works on NO₃. Thus a more complete conversion of influent nitrogen in nitrogen gas and, consequently, a better effluent quality resulted in the open-loop.

It can therefore be concluded that the present fuzzy-logic controller, despite its effectiveness in minimizing N_2O emissions, is not sufficient alone in order to meet contextually the effluent nitrogen requirement. Hence, results suggest that a strategy controlling the TN removal efficiency is applied to the system as well in order to avoid compromising the effluent quality. With regard to this, one possible solution could be to add biodegradable organic carbon on top of the first anoxic tank (ANOX1) according to the amount of nitrogen oxides to be reduced. In alternative, the anoxic hydraulic retention time could be increased by manipulating the internal recycle flow rate.

5. CONCLUSIONS AND FUTURE PERSPECTIVES

A novel control strategy aiming at reducing the total amount of N₂O emitted from domestic wastewater treatment plants has been developed in this work. The control strategy is based on reducing nitrite accumulation, which would trigger the production of N₂O by both AOB and by HB. This is achieved by controlling in the aerobic zone the ratio between NOB-produced nitrate and AOB-consumed ammonium (R_{NatAmm}) at its optimal value, which was identified to be around 1. The oxygen mass transfer coefficient, directly proportional to the oxygen supply, was chosen as manipulated variable. The controller was built up in the simulation environment Simulink and then tested in the newly-developed Benchmark Simulation Model Nº2 for Nitrous oxide (BSM2N). The closed-loop simulation results were benchmarked against the open-loop results. The comparison revealed that the controller was able to effectively reduce the N₂O emissions by 35% by enhancing the NOB activity. At the same time effluent quality decreased drastically. It is therefore suggested that the present controller should be coupled with another controller for the

achievement of a complete heterotrophic denitrification of nitrogen oxides either by regulating the amount of organic carbon externally added on top of the anoxic zone or by decreasing the internal recycle flow rate. Lastly, given the fact that the model does not include the N₂O-production pathway related to incomplete oxidation of hydroxylamine, the controller can be stated to be adequate only for the reduction of N₂O production during AOB and HB denitrification, which however can be considered the predominant N₂O contributors. Further evidences for the model description of the missing pathway need to be achieved.

Acknowledgements

The research was funded through the Research Project LaGas (12-132633).

References

- M.R.J. Daelman, E.M. van Voorthuizen, U.G.J.M. van Dongen, E.I.P. Volcke, M.C.M. van Loosdrecht, Seasonal and diurnal variability of N2O emissions from a full-scale municipal wastewater treatment plant, Sci. Total Environ. 536 (2015) 1–11.
- [2] J. Foley, D. de Haas, Z. Yuan, P. Lant, Nitrous oxide generation in full-scale biological nutrient removal wastewater treatment plants., Water Res. 44 (2010) 831–44.
- Y. Law, L. Ye, Y. Pan, Z. Yuan, Nitrous oxide emissions from wastewater treatment processes., Philos. Trans. R. Soc. Lond. B. Biol. Sci. 367 (2012) 1265–77.
- [4] T. Aoi, Y. Okaniwa, K. Hagiwara, K. Motomura, E. Iwaihara, M. Imai, et al., A direct ammonium control system using fuzzy inference in a high-load biological denitrification process treating collected human excreta, Water Sci. Technol. 26 (1992) 1325– 1334.
- [5] R. Boiocchi, M. Mauricio-Iglesias, A.K. Vangsgaard, K.V. Gernaey, G. Sin, Aeration control by monitoring the microbiological activity using fuzzy logic diagnosis and control. Application to a complete autotrophic nitrogen removal reactor, J. Process Control. 30 (2015) 22–33.
- [6] R.M. Tong, M.B. Beck, A. Latten, Fuzzy Control of the Activated Sludge Wastewater Treatment Process, Automatica. 16 (1980) 695–701.
- [7] R. Boiocchi, K. V Gernaey, G. Sin, Extending the benchmark simulation model no2 with processes for nitrous oxide production and side-stream nitrogen removal, in: 12th Int. Symp. Process Syst. Eng. 25th Eur. Symp. Comput. Aided Process Eng., Elsevier, 2015: pp. 2477–2482.
- [8] U. Jeppsson, M.-N. Pons, I. Nopens, J. Alex, J.B. Copp, K. V Gernaey, et al., Benchmark simulation

model no 2: general protocol and exploratory case studies., Water Sci. Technol. 56 (2007) 67–78.

- [9] M. Henze, C.P.L.G. Jr, W. Gujer, G.V.R. Marais, T. Matsuo, A general model for single-sludge wastewater treatment systems., Water Res. 21 (1987) 505–515.
- [10] L. Guo, P.A. Vanrolleghem, Calibration and validation of an activated sludge model for greenhouse gases no. 1 (ASMG1): prediction of temperature-dependent N2O emission dynamics., Bioprocess Biosyst. Eng. 37 (2014) 151–163.
- [11] G. Tallec, J. Garnier, G. Billen, M. Gousailles, Nitrous oxide emissions from secondary activated sludge in nitrifying conditions of urban wastewater treatment plants: Effect of oxygenation level, Water Res. 40 (2006) 2972–2980.
- [12] A. Aboobakar, E. Cartmell, T. Stephenson, M. Jones, P. Vale, G. Dotro, Nitrous oxide emissions and dissolved oxygen profiling in a full-scale nitrifying activated sludge treatment plant, Water Res. 47 (2013) 524–534.
- [13] V. Rassamee, C. Sattayatewa, K. Pagilla, K. Chandran, Effect of oxic and anoxic conditions on nitrous oxide emissions from nitrification and denitrification processes, Biotechnol. Bioeng. 108 (2011) 2036–2045.
- [14] K.E. Mampaey, B. Beuckels, M.J. Kampschreur, R. Kleerebezem, M.C.M. van Loosdrecht, E.I.P. Volcke, Modelling nitrous and nitric oxide emissions by autotrophic ammonia-oxidizing bacteria, Environ. Technol. 34 (2013) 1555–1566.
- [15] M.J. Kampschreur, N.C.G. Tan, R. Kleerebezem, C. Picioreanu, M.S.M. Jetten, M.C.M. Van Loosdrecht, Effect of dynamic process conditions on nitrogen oxides emission from a nitrifying culture, Environ. Sci. Technol. 42 (2008) 429–435.
- [16] M. Pocquet, Z. Wu, I. Queinnec, M. Spérandio, A two pathway model for N2O emissions by ammonium oxidizing bacteria supported by the NO/N2O variation., Water Res. 88 (2015) 948–959.
- [17] H.M.S. Lababidi, C.G.J. Baker, Fuzzy Modeling, in: Handb. Food Bioprocess Model. Tech., 2006: pp. 451–498.
- [18] C. Glass, J. Silverstein, J. Oh, Inhibition of denitrification in activated sludge by nitrite, Water Environ. Res. 69 (2014) 1086–1093.
- [19] K. V. Gernaey, X. Flores-Alsina, C. Rosen, L. Benedetti, U. Jeppsson, Dynamic influent pollutant disturbance scenario generation using a phenomenological modelling approach, Environ. Model. Softw. 26 (2011) 1255–1267.