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Review

Advanced strategies to improve nitrification process in sequencing batch reactors - A review

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A B S T R A C T

The optimization of biological nitrogen removal (BNR) in sequencing batch reactors has become the aim of researchers worldwide in order to increase efficiency and reduce energy and operating costs. This research has focused on the nitrification phase as the limiting reaction rate of BNR. This paper analyzes different strategies and discusses different tools such as: factors for achieving partial nitrification, real-time control and monitoring for detecting characteristic patterns of nitrification/denitrification as end-points, use of modeling based on activated sludge models, and the use of data-driven modeling for estimating variables that cannot be easily measured experimentally or online. The discussion of this paper highlight the properties and scope of each of these strategies, as well as their advantages and disadvantages, which can be integrated into future works using these strategies according to legal and economic restrictions for a more stable and efficient BNR process in the long-term.

Contents

1. Introduction

Several industries discharge wastewater with high nitrogen concentrations, such as the petrochemical, fertilizer and food industries (Carrera et al., 2003). Nitrogen is mainly presented as ammonia, nitrite and nitrate, which causes dissolved oxygen (DO) depletion (Van Hulle et al., 2010), produces toxicity in aquatic fauna (Pauer and Auer, 2009) and enhances the eutrophication processes

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List of abbreviations

ANN	Artificial neural network
AOB	Ammonia-oxidizing bacteria
ARE	Ammonia removal efficiency
ASM	Activated sludge model
BNR	Biological nitrogen removal
COD	Chemical oxygen demand
DO	Dissolved oxygen
EFuNN	Evolving fuzzy neural network
FA	Free ammonia
FNA	Free nitrous acid
FNN	Fuzzy neural network
GP	Gaussian process
IDP	Iterative dynamic programming
IWA	International water association
MPCA	Multiway principal component analysis
MSC	Moving slope change
NLR	Nitrogen loading rate
NOB	Nitrite-oxidizing bacteria
ORP	Oxidation reduction potential
OUR	Oxygen uptake rate
PID	Proportional-integral-derivative
SBR	Sequencing batch reactor
SOM	Self-organizing map
SQP	Successive quadratic programming
SRT	Sludge retention time
SVM	Support vector machine
WWTP	Wastewater treatment plant

(Wiesmann et al., 2007). Moreover, the ingestion of water with high nitrite/nitrate concentrations might cause methemoglobinemia in infants (Wiesmann et al., 2007) and increase the formation of carcinogenic nitrosamines (Rodríguez et al., 2011b).

A commonly used and economically viable alternative for the treatment of industrial and municipal wastewater is the biological nitrogen removal (BNR) process (Zanetti et al., 2012), which involves two sub-processes: nitrification (aerobic respiration) and denitrification (anoxic respiration). The BNR process can achieve high efficiency, low consumption of external organic matter and low surplus sludge (Boaventura et al., 2001). The operating costs involve energy costs for aeration, reagents like alkaline solution and exogenous chemical oxygen demand (COD) (Yan and Hu, 2009) and costs associated with sludge management (Singh and Srivastava, 2011).

Among the conventional BNR systems used, various reactor configurations are differentiated by the availability of biomass in their interior (Von Sperling, 2007): suspended biomass in the bulk liquid (activated sludge reactors, membrane bioreactors, sequencing batch reactors (SBRs)) or immobilized biomass over an inert support (e.g., polyethylene biodiscs, polyurethane foam (Singh and Srivastava, 2011)) or a granule (trickling filter, submerged aerated biofilter, rotating biological contactor) as well as by their modes of operation: continuous or batch.

The SBR stands out for its flexibility and low installation cost (Marsili-Libelli et al., 2008), in addition to having the advantage of BNR occurring in only one reactor through the sequential development of aerobic (nitrification), anoxic (denitrification) and settling phases (Poo et al., 2006). In a SBR the efficiency and energy consumption in terms of the nitrification and denitrification reactions will depend on environmental conditions (e.g., pH, temperature, DO, oxidation reduction potential (ORP)) and operational ones (e.g., feed pattern, sludge retention time (SRT), cycle length) during each reaction phase. Therefore, all these operating strategies present a series of challenges: 1) reduction of cycle length, 2) minimization of energy costs, 3) stabilization of efficiency on a long-term basis, taking into account the compliance of local legislation for nitrogen removal. In order to reach the proposed objectives, interdisciplinary operating strategies have been designed, including the development of partial nitrification, real-time control, mathematical modeling, data-driven based modeling and artificial intelligence.

In this paper, a review of several strategies applied to produce BNR in SBRs are discussed, focusing mainly on tools used for optimizing nitrification (aerobic phase) as the rate-limiting step in the overall BNR process. This is based on the intrinsic behavior of BNR, where nitrification products are further used as reactants for denitrification (Kirchman, 2012), implying that an efficient nitrification represents the first goal for developing an efficient denitrification. Most of the revised works are mainly based on suspended biomass SBRs, although in some cases the review extends over other reactor configurations.

This article is organized as follows. In Section 2, the concept of BNR through the nitrification-denitrification process and the concept of partial nitrification are introduced. In Section 3, the SBR concept, operation modes and their application to the BNR process are presented. In Section 4, activated sludge models (ASMs) are presented as a tool for dynamic simulation, a state estimator and optimization of BNR processes. In Section 5, a technique called bending-points detection is described, which can reduce operating costs by estimating the phase length for nitrification and denitrification. In Section 6, several data driven-based modeling techniques are introduced, which are able to estimate critical variables of the nitrification-denitrification process, with the aim of monitoring the process, improving efficiency and reducing costs. Finally, in Section 7 conclusions are given.

2. Biological nitrogen removal and partial nitrification

Nitrogen removal through nitrification-denitrification is a widely studied process and is one of the most frequently practiced process for removing nitrogen from wastewaters (Ruiz et al., 2006; Wiesmann et al., 2007). Compared to physical-chemical treatments, it seems to be more effective and relatively cheap (Guo et al., 2010). In nitrification under aerobic conditions, ammonium (NH_4^+) is transformed into nitrite (NO_2^-) by means of ammonia-oxidizing bacteria (AOB) in alkaline conditions. Subsequently, nitrite is transformed into nitrate (NO_3^-) by means of nitrite-oxidizing bacteria (NOB) (Antileo et al., 2006). Afterwards, the denitrification process under anoxic conditions and via easily biodegradable organic matter converts this nitrate into nitrite, then to nitric oxide (NO), then to nitrous oxide (N_2O), and finally to molecular nitrogen (N_2), which is innocuous (Mokhayeri et al., 2008; Rodríguez et al., 2011b).

Since the nitrite is formed and consumed by nitrification and formed again during denitrification, the nitrite oxidation becomes an unnecessary step (Antileo et al., 2006). Hence, the concept of partial nitrification or shortcut biological nitrogen removal emerges as an attractive alternative (Claros et al., 2012).

To carry out nitrite accumulation it is necessary to enhance the activity of the AOB and to selectively reduce/inhibit the activity of the NOB (Guo et al., 2010; Zeng et al., 2009), also called NOB washout (Jubany et al., 2009). Nitrite accumulation can be achieved through the control of the following environmental variables: pH, DO, temperature, SRT (Bae et al., 2001) and reaction time (Pambrun et al., 2008). Once nitrite is accumulated, it can be directly denitrified (Sinha and Annachhatre, 2007) (Fig. 1). A big challenge during partial nitrification is to achieve a stable depletion of NOB activity on a long-term basis (months) (Fu et al., 2010; Guo et al., 2009).

In the literature, it is mentioned that the approach of partial nitrification saves approximately 25% of aeration costs during the nitrification phase (Blackburne et al., 2008; Ciudad et al., 2005) and 40% of organic matter during the denitrification phase (Wei et al., 2014) in addition to decreasing the surplus sludge production (Pambrun et al., 2008).

3. Sequencing batch reactor

A SBR cycle is characterized by a series of phases which are principally fill, react, settle and draw, where each of these phases has a defined time (Wilderer et al., 2001). The operation of SBR begins with the fill phase, the reactor is filled and stirring and oxygenation are applied leading to the reaction phase. This stage can be further divided into two, aerobic and anoxic. In the settle phase, stirring is removed to allow settlement of the sludge. The next step is the draw phase, where the effluent is discharged. Once the reactor is emptied, a new cycle starts by filling the reactor again. For each new cycle, aerobic/anoxic phases duration could differ depending on the operational needs of the wastewater treatment plant (WWTP). Specifically, the sequence of phases is defined in function of the influent characteristics and effluent requirements according to environmental standard policies (Fuentes et al., 2010; Shammas and Wang, 2009).

Referring to the suspended biomass SBR certain characteristics must be mentioned; it is a system that is severely affected by uncertainties (Guo and Li, 2013). Batch-to-batch it exhibits some variations in the microbiological distribution, non-linear and time-variant dynamic behavior due to the diversity and kinetics of autotrophic and heterotrophic communities (Chen and Liu, 2002; Lee et al., 2005). Additionally, batch processes are notably subject to significant disturbances such as hydraulic changes, variability in the concentration of the inlet flow, change in microbial activity from batch-to-batch (Aguado et al., 2007; Yoo et al., 2006), equipment/instrumentation failures (e.g., blower, mixer, influent pump, nitrogen sensors) (Caccavale et al., 2010; Kim et al., 2006), and deterioration of the closed-loop control performance (e.g., DO closed-loop control) (Muñoz et al., 2009). Furthermore, small changes in concentrations or flows among batch cycles can affect the kinetics of non-linear biological reactions, which leads to variability in effluent quality and sludge growth (Yoo et al., 2004), making it difficult to maintain the performance of the designed operation strategies over the SBR over the long-term.

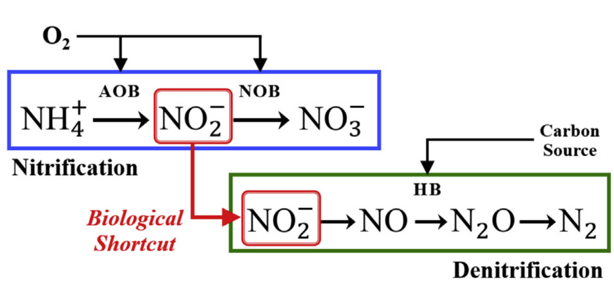

Fig. 1. Scheme of partial nitrification process by using shortcut between nitrification and denitrification.

A remarkable feature of SBR processes is the possibility of implementing an automatic control and monitoring of the reaction time (aeration/mixing times) in order to make adjustments according to the wastewater quality requirements. This feature (in case of aerobic phase) also may be complemented with aeration control strategies, which can be divided in two types: continuous aeration and intermittent aeration (Li et al., 2011). All of these operation possibilities improve the efficiency and energy savings of WWTPs, but they also entail more complex operation modes that require highly reliable automation methods (Yang et al., 2010).

The total cycle time in the SBR is the sum of the lengths of its phases. In a conventional SBR operation, each phase has a fixed duration regardless of the process dynamics and the nitrogen concentration in the influent. In terms of energy consumption costs, this may result in a highly inefficient operation (Marsili-Libelli, 2006; Zhu et al., 2009). Therefore, the advanced monitoring and control tools have been steadily applied to adapt the reaction time of the aerobic/anoxic phases to the particular requirements of the effluent quality (Marsili-Libelli et al., 2008). The accuracy for estimating the length of each phase is critical due to the non-linearity of the bacterial growth kinetic and the uncertainties inherent to the SBR process, which means the advanced monitoring tools must be able to adapt to the previously mentioned drawbacks in order to avoid two undesirable scenarios: insufficient reaction times leading to an incomplete nitrogen removal and longer than necessary phase lengths increasing the operating costs (e.g., aeration and external organic matter consumption) (Wilderer et al., 2001; Yoo et al., 2006). In both cases, the AOB/NOB ratio might be affected, leading to an unstable partial nitrification on a long-term basis.

3.1. Nitrification-denitrification applied in SBRs

Most BNR practices have focused on the SBR operation for the treatment of domestic and industrial wastewater. One of these studies was reported by Ra et al. (2000), where a piggery manure wastewater treatment system and operating strategies that minimize costs were implemented. Their results showed a nitrogen removal of around 97% for an average influent ammonium concentration of 250 mg NH_4^+ −N/L. In Obaja et al. (2003) a piggery wastewater treatment was studied, the nitrogen concentration of which was as high as 1500 mg NH_4^+−N/L, achieving a removal performance of 99.7%. In Rodríguez et al. (2011a), the authors treated a combination of two types of wastewater from a meat product processing company with different ammonium concentrations (average values 365 and 616 mg NH_4^+−N/L), by several experiments varying the proportions of each type of wastewater they achieved removal efficiencies up to 71%. Guo et al. (2011) reported a nitrogen removal up to 78% at 89 mg NH_4^+−N/L initial concentration. At full-scale SBR, Fernandes et al. (2013) used domestic wastewater with an ammonium concentration of 45.9 mg NH_4^+−N/L, obtaining an average of 61% of removal efficiency. A summary of the above research is presented in Table 1.

3.2. Partial nitrification in SBRs

Partial nitrification has also been successfully applied in SBRs. In Ciudad et al. (2005) the effect of DO on nitrite accumulation was reported, showing that at 1.4 mg O_2/L, 75% of nitrite accumulation and 95% of ammonia removal occurred after 170 days of operation. On the other hand, Sinha and Annachhatre (2007) reviewed several works related to partial nitrification, where they found that a SBR operated at high temperatures (>25 °C), with a pH in the range 7.5–8.5 and DO < 0.5 mg O_2/L can accumulate nitrite. Moreover, in Yang et al. (2007), a strategy for partial nitrification at low

Table 1
Research into nitrification-denitrification applied in SBRs.

Publication	Wastewater source	Nitrogen removal	Validation time
Ra et al. (2000)	Piggery industry	97%	Around 117 days
Obaja et al. (2003)	Piggery industry	99.7%	N/A
Rodríguez et al. (2011a)	Meat products processing company	71%	252 days
Guo et al. (2011)	Synthetic wastewater	78%	Around 70 days
Fernandes et al. (2013)	Domestic wastewater	61%	180 days

Validation time: Time in which nitrification-denitrification was experimentally carried out.
N/A: Information not available.

temperatures based on a DO and a real-time control during the aerobic phase was performed, obtaining a stable partial nitrification for a long period of 180 days and a nitrite accumulation rate above 95%. Additionally, in Galí et al. (2007) the optimal operating conditions to achieve nitrogen removal via nitrite accumulation for the treatment of reject water (800–900 NH_4^+–N/L) was found at pH between 7.5 and 9.0, DO below 1.0 mg O_2/L, temperature of 32 °C and a cycle length of 8 h leading to a nitrogen removal of 0.8 kg N/d•m^3. Guo et al. (2010) reported that the degradation ammonium rate decreased 1.5 times when the temperature was reduced from 25 to 15 °C; however, at low temperatures (12–17 °C) there was no deterioration in nitrite accumulation, achieving an efficiency of 95% in two months of SBR operation. Furthermore, Yuan et al. (2010) assessed the effects of intermittent aeration, pH, temperature, DO, and SRT. The best conditions to ensure partial nitrification were pH between 7.5 and 8.0, temperature between 30 and 40 °C, DO between 1.0 and 1.5 mg O_2/L and a SRT higher than 15 days. Additionally, in Li et al. (2011), during 180 days of operation and using an influent with 300 mg NH_4^+–N/L, it was found that for a SRT working longer than 100 days, with intermittent aeration, a temperature around 20 °C and a pH between 7.1 and 7.4, 90% of nitrite accumulation was achieved. In another work, Sun et al. (2015) combined free ammonia (FA) inhibition for NOB growth with real-time control during the aerobic phase (based on DO, pH and ORP measures) to successfully achieve partial nitrification under low operating temperatures (13.0–17.6 °C). Finally, in Soliman and Eldyasti (2016) a DO control strategy using a reactor with variable mixing speed was implemented, a system consisting of high temperature and pH, FA/free nitrous acid (FNA) inhibitions and with different feeding strategies, was able to achieve ammonia removal efficiency (ARE) of 99% and nitrogen loading rate (NLR) of 93%. A summary of the analyzed parameters and the results of the partial nitrification experiments are presented in Table 2.

As can be seen in Table 2, most research on partial nitrification has focused mainly in suspended biomass systems rather than in biofilm ones. Regarding to this, optimal relationships among oxygen mass transport-biofilm thickness/bulk DO concentrations should be pursued in future works in order to strongly limit the NOB/AOB ratio in biofilm systems.

Partial nitrification in BNR is of great importance from the point of view of operating costs (subject to legislation compliance), which is shown by the efforts of different investigations into operating strategies to maintain nitrite accumulation at high levels. The application of an advanced automatic control based on process simulation and AOB/NOB monitoring using molecular tools will be the new challenges to overcome in this issue so as to achieve a stable partial nitrification on a long-term basis.

4. Activated sludge models

Biological wastewater treatments are complex systems involving physical, chemical and biological processes. Not all variables can be measured or estimated reliably. Therefore, mathematical models offer a quantitative evaluation of these critical variables (Ferrer et al., 2008). For the purposes of creating a common nomenclature of BNR models, the International Water Association (IWA) produced some phenomenological models called ASMs (Henze et al., 2000), which include: ASM1 (Henze et al., 1987), ASM2 (Gujer et al., 1995), ASM2d (Henze et al., 1999) and ASM3 (Gujer et al., 1999). The ASM1 describes the complex processes related to the removal of carbon and nitrogen removal from municipal wastewater (Wiesmann et al., 2007). The ASM2 is an extension of the ASM1, this model includes many more components to characterize the biological phosphorus and nitrogen removals (Bagheri et al., 2016; Henze et al., 1999). The ASM2d is built from the ASM2 and includes the denitrifying activity of phosphorus accumulating organisms (Gernaey et al., 2004). The ASM3 was developed to correct some limitations of ASM1, together with

Table 2
Operating parameters used to achieve partial nitrification.

Publication	Biomass growth method	Operating Parameters	Results	Validation time
Ciudad et al. (2005)	Suspended biomass	DO	75% Nitrite accumulation 95% Ammonia removal	170 days
Sinha and Annachhatre (2007)	Both suspended and biofilm biomass systems are reviewed	pH, DO, and temperature	Nitrite accumulation was possible	N/A
Yang et al. (2007)	Suspended biomass	DO and length of the aerobic phase	180 days of stable nitrification	180 days
Galí et al. (2007)	Suspended biomass	pH, DO, temperature, and cycle length	Nitrogen removal of 0.8 kg N/d•m^3	1-2 months
Guo et al. (2010)	Suspended biomass	Temperature	Nitrite accumulation was higher than 90%	135 days
Yuan et al. (2010)	Suspended biomass	pH, temperature, DO, and SRT	Best operational conditions to accomplish partial nitrification	At least 7 days
Li et al. (2011)	Suspended biomass	pH, intermittent aeration, temperature, and SRT	Nitrite accumulation of 90%	180 days
Sun et al. (2015)	Suspended biomass	FA inhibition and aerobic reaction duration	NOB limitation growth under low temperatures	233 days
Soliman and Eldyasti (2016)	Suspended biomass	DO, temperature, feeding strategy, pH, and FA/FNA inhibitions	Ammonia removal efficiency of 99%	130 days

Validation time: Time in which partial nitrification was experimentally carried out.
N/A: Information not available.

including storage of organic substrates as a new process (Gujer et al., 1999).

ASMs are generally used for state estimation, simulation (or description) of WWTPs, BNR optimization (energy use, cycle length and/or reagents use), state predictions, and design of automatic control strategies. In the literature, the work by Boaventura et al. (2001) for state estimation reported the development of state observers based on Extended Kalman Filter (Chui and Chen, 2009) in order to estimate the concentration of heterotrophic biomass, autotrophic biomass, nitrate, ammoniacal nitrogen and carbonaceous substrates. An example of BNR optimization is the work by Coelho et al. (2000), where a model-based optimization was applied to minimize the total batch time in a SBR using constrained successive quadratic programming (SQP) (Floudas and Pardalos, 2008) as the optimization algorithm, and the feed rate profile, fill time and aeration time as decision variables. On the other hand, in Corominas et al. (2006) an ASM1 was used to evaluate the SBR performance under control strategies (DO control, phase length control) and no control strategy, where the effluent quality, the energy required for aeration and the treatment capacity were used as performance indices. Furthermore, Kim et al. (2008) aimed to maximize both the nitrogen removal and removal efficiency based on a performance index that incorporates the total area under the trajectory curves of DO and nitrogen concentrations. This optimization might be implemented through a simplified ASM1 and iterative dynamic programming (IDP) (Luus, 2000). Cho et al. (2010) used a modified ASM1 for maximizing nitrogen removal; the effects of feed pattern fill and aeration type were also studied. Regarding the use of ASMs to describe wastewater plant behavior and to predict state variables in a BNR processes, Pambrun et al. (2006) formulated a complete model able to describe the short-term dynamics of two-step nitrification and predict the partial nitrification efficiency in a SBR fed at a high inlet ammonia concentration. Magrí and Flotats (2008) calibrated a model to simulate the nitrification-denitrification processes for treating the liquid fraction of pig slurry, where the calculated concentrations of DO, NH_4^+, NO_2^-, and NO_3^- were compared with experimental data. In Cruz-Bournazou et al. (2012) a model reduction (to a nine-state, six-state and five-state version) of an extended-ASM3 was proposed, which reduced the calculation time while maintaining its accuracy. A summary of ASMs applications in SBRs are presented in Table 3. In another work, and using a reduced five-state version of an extended-ASM3, Cruz-Bournazou et al. (2013) developed an optimization framework which searches an optimal intermittent aeration profile in order to minimize both the operation time and the energy required for aeration of a SBR cycle under partial nitrification. Moreover, in Soliman and Eldyasti (2017) implemented and calibrated a model of a lab-scale SBR using Biowin® software to describe the long-term dynamic behavior of the partial nitrification process.

All the aforementioned studies show the potential of ASMs for modeling the biological reaction in a BNR process. By contrast, there is a lack of studies on SBR performance throughout multiple consecutive operation cycles, and the effect associated with the uncertainty of the model parameters has not yet been studied. It is necessary to predict and control critical operation variables of the BNR process more reliably so as to affect microbiology dynamics of the AOB/NOB on a long-term basis.

5. Bending-points detection

Nowadays nitrogen control systems are mainly based on online ammonium/nitrate analyzers (Ruano et al., 2012), thereby allowing them to provide valuable information about the status of the plant, which can be used by the operator to implement real-time control strategies and thus optimize the process performance (Claros et al., 2012; Huang et al., 2010). Aerobic phase length control and DO control are examples of strategies based on online measurements of ammonium, which have been proposed for energy savings (Hajji et al., 2016; Olsson, 2012). Nevertheless, the major disadvantages of these analyzers are their high investment and maintenance costs (Casellas et al., 2006; Ruano et al., 2009), significant time delay (Cecil and Kozlowska, 2010), and complex operation (Yang et al., 2010). To overcome these drawbacks several researchers have online monitored physical-chemical parameters such as DO, pH, ORP (Akin and Ugurlu, 2005; Won and Ra, 2011) and oxygen uptake rate (OUR) (Puig et al., 2005) (also called secondary variables) which can be used to estimate the duration of the nitrification and denitrification phases.

Bending-points detection is a strategy that uses secondary variables like those previously mentioned to determine the lengths of the aerobic/anoxic phases in a SBR in order to save energy and process capacity (Ruano et al., 2012). When pH, DO, ORP and OUR are not closed-loop controlled, it is possible identify relative changes (bending-points) in their profiles during aerobic/anoxic reactions. These bending-points in the secondary variables profiles are used to determine the end-point of each reaction phase (Wu et al., 2007), which leads to a reduction in aeration costs and

Table 3
Applications of ASMs in SBRs.

Publication	ASM application	Variables involved
Boaventura et al. (2001)	State observer was used for BNR modeling	Dissolved and particulate concentrations of all organic/nitrogen compounds
Coelho et al. (2000)	ASM used for BNR optimization	Minimization of the total batch time
Corominas et al. (2006)	Evaluation SBR performance	Performance indices: the effluent quality, the required energy for aeration and wastewater flow
Kim et al. (2008)	Nitrogen removal and energy efficiency maximization	Nitrogen removal and energy efficiency
Cho et al. (2010)	BNR optimization	Optimization of the nitrogen removal
Pambrun et al. (2006)	Process description and prediction	Nitrification description and partial nitrification prediction
Magrí and Flotats (2008)	Nitrification-denitrification simulation	DO, pH, NH_4^+, NO_2^-, and NO_3^- predictions
Cruz-Bournazou et al. (2012)	Extended ASM3 for a model simplification	Nine-state, six-state and five-state models
Cruz-Bournazou et al. (2012)	Optimal intermittent aeration profile to minimize both the operation time and the energy required for aeration	Optimization parameters: Equal length for all aeration intervals, equal length for all anoxic intervals, and the duration of the last aeration interval of the intermittent aeration profile
Soliman and Eldyasti (2017)	Calibrated model to describe the long-term dynamic behavior of the partial nitrification process in a lab-scale SBR	A reduced five-state version of an extended-ASM3

reaction time (Antileo et al., 2013; Casellas et al., 2006; Puig et al., 2005). Since in the long-term a sustained increase in NOB populations might occur in the reactor, researchers face the challenge of limiting/inhibiting NOB growth to reach a stable nitrite accumulation over time (Guo et al., 2009). In Fig. 2 a scheme is presented of the sensors involved in the detection of the bending-points for both the aerobic and anoxic phases.

The bending-points commonly associated with nitrification in the aerobic phase are as follows: ammonia valley for pH (Peng et al., 2006; Traoré et al., 2005) (Fig. 3A), plateau for ORP (Peddie et al., 1990; Poo et al., 2006) (Fig. 3B), elbow for DO (Li et al., 2011; Martín de la Vega et al., 2012) (Fig. 3C) and changes in the OUR profile Paul et al. (1998); Puig et al. (2005) (Fig. 3D). In the case of denitrification they are: nitrate knee for ORP Holman and Wareham (2002); Wang et al. (2013) (Fig. 3E) and nitrate apex for pH (Rubio et al., 2004; Zeng et al., 2008) (Fig. 3F). The principal problem lies in the fact that the bending-points may be significantly affected (it does not appear in the profiles of the measured variables) by feed pattern, variations of inlet concentrations, changes in environmental parameters or measurement noise in the reactor (Poo et al., 2006).

On the other hand, and as mentioned above, bending-points detection acts upon variables with no closed-loop control, making its application to partial nitrification difficult since pH and DO closed-loop control has to be used to limit/inhibit the NOB growth. However, some studies have applied bending-points detection to promote partial nitrification (Antileo et al., 2013; Gu et al., 2012). Fig. 4 displays the manipulated variables carbonate consumption (total number of sodium carbonate pulses injected to the reactor) and air valve opening (percentage of opening) of the pH and DO closed-loop control during aeration phase of a BNR process conducted in a laboratory scale SBR (Antileo et al., 2013). The novelty of these approaches has been in finding patterns in the manipulated variables when pH and DO are subjected to a proportional-integral-derivative (PID) feedback control during nitrification in a SBR.

The works reported in this issue aim to study the application of several strategies to achieve an efficient detection under different operating conditions where the closed-loop control of pH and DO is not used. For instance, in Pavšelj et al. (2001) the derivatives of filtered online signals of pH and DO were used, where the bending-points criteria were when two local maximums were noted in the DO derivative and the pH derivative fell under a certain value. Puig et al. (2005) detected the end-point once the online measured OUR reached a minimum OUR value. Moreover, in Poo et al. (2006) different bending-points criteria for each of the measured variables were studied: for ORP Δ^2ORP ≈ 0 and ΔORP ≈ 0 were used, for pH when a pH increase was observed, for DO when a threshold was reached or a DO increased in its profile. In addition, both in Guo et al. (2007) and Kishida et al. (2008) the pH derivative was used as a decision parameter and a sharply changing value from negative to positive as the bending-point. By contrast, in Ga and Ra (2009) a method called a moving slope change (MSC) was applied to the pH profile; therefore, when the MSC reached a value of -0.3, the aerobic phase was finished.

Artificial intelligence was used in Cohen et al. (2003), where a classifier based on artificial neural networks (ANNs) (Haykin, 2011) was created, which used geometric features from the DO profiles as inputs. And in order to make the bending-points detection more robust, they developed a system based on evolving fuzzy neural networks (EFuNN) (Kasabov, 2001). These allow the classifier to adapt to new patterns generated by each newly performed SBR cycle. On the other hand, Marsili-Libelli (2006) proposed a pattern recognition system based on fuzzy clustering (Babuška, 2012) of the filtered derivatives of pH, DO and ORP. Machón-González and López García (2006) proposed a combination of self-organizing maps (SOM) (Kohonen, 2012) and K-means (Duda et al., 2012) to detect the aerobic end-point in a coke WWTP by using the selected variables of DO, % air valve opening (manipulated variable of the installed DO controller) and temperature. Marsili-Libelli et al. (2008) also developed a fuzzy inference system (Sivanandam et al., 2006) based on the first derivative of pH and DO profiles and also included the second derivative of the ORP profile to decide when the aerobic phase ended. Moreover, in Luccarini et al. (2010) an algorithm based on ANNs was developed to identify representative patterns ("apexes", "knees", and "steps") related to the end of nitrification and denitrification.

Regarding methodologies based on statistical and probabilistic models, Villez et al. (2010) applied Hotelling's statistic (Ye, 2013) with the information obtained from a model generated with five process variables (air flow rate and the derivatives of air flow rate, pH, DO and ORP) to estimate the length of the aerobic phase. Kocijan and Hvala (2013) proposed a Gaussian process (GP) Rasmussen (2004) model to estimate the length of the phases in the SBR cycle; the GP was used for both the smoothing and classifying of online measured variables (pH, DO, and ORP).

Recent works have used pH and DO closed-loop control in SBRs.

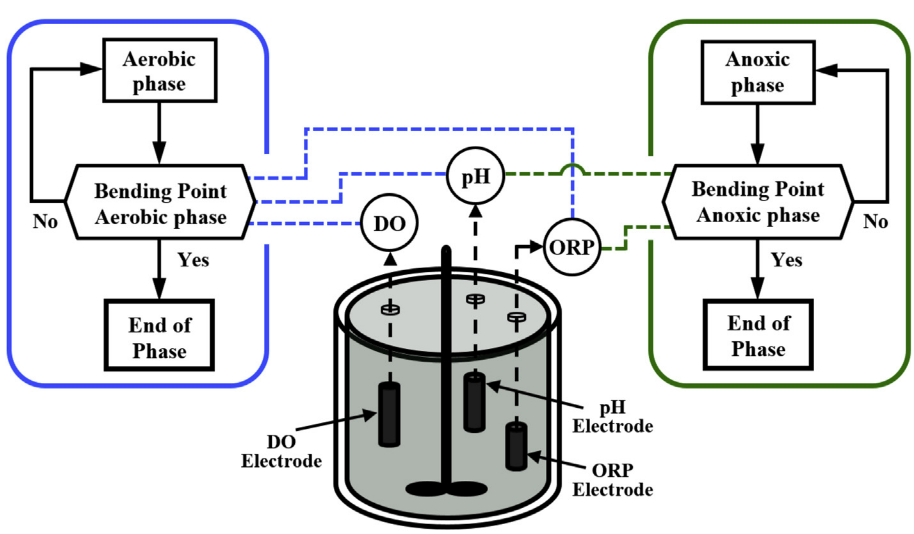

Fig. 2. SBR instrumentation scheme for bending-points detection.

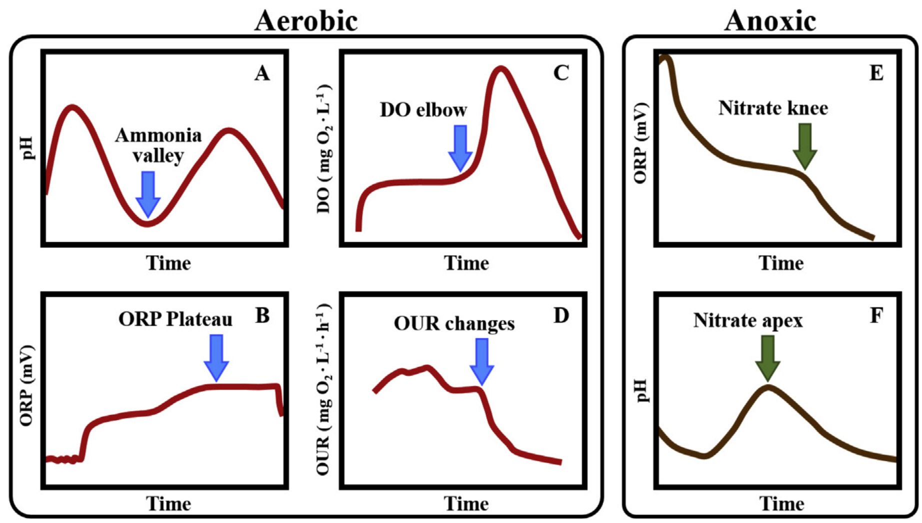

Fig. 3. Bending points for nitrification (A–D) and denitrification (E–F), where arrows show the specific bending point for each parameter profile. Adapted from Puig et al. (2005) and Poo et al. (2006).

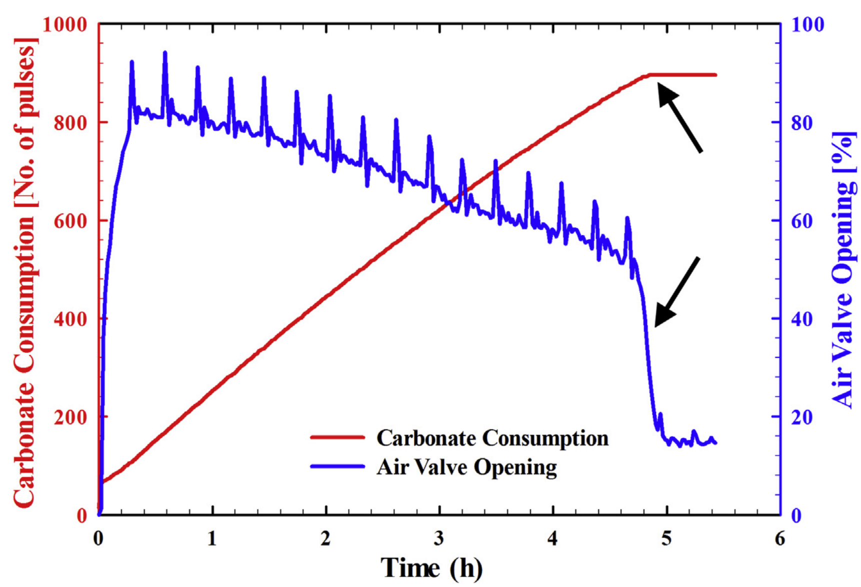

Fig. 4. Example of bending points for nitrification based on a closed-loop control technique on the secondary variables pH and/or DO, where arrows show bending points being measured in a laboratory process.

In Gu et al. (2012) the DO in the reactor was controlled by a centrifugal blower equipped with a frequency converter; consequently, a strategy that involved the application of MSC to the blower frequency data and defining a MSC value equal to −1 as the end-point criterion was designed and evaluated. In other study, employing the profiles of the manipulated variables pH (carbonate consumption) and DO (percentage of air valve opening) (Antileo et al., 2013), determined the end of the aerobic phase when carbonate consumption remained constant for 30 min and air valve opening reached a value of 25%. And in a more recent article (Jaramillo et al., 2018), proposed a strategy based on feature extraction over the manipulated variables of the pH and DO controller together with support vector machines (SVMs) classification to estimate the aerobic phase length. Table 4 summarizes the previously reviewed strategies.

These strategies take information from derivatives shown to be effective, but care should be taken with some issues that can affect the discriminant information obtained from them: sensors affected by noise and variations in the operating/environmental conditions in the reactor. Regarding the methodologies based on artificial intelligence and statistical/probabilistic models, these respond efficiently to the operating conditions/characteristics for which they were trained, but they do not appear to work effectively in the long-term due to the non-linear and time-variant characteristics presented in the nitrogen removal process applied to SBRs.

Finally, there are still not many studies that use a closed-loop control technique on the secondary variables pH and/or DO in order to achieve partial nitrification. In these cases, the bending-points detection methods must use the manipulated variables of the process in order to obtain information related to nitrogen removal dynamics. Linking online monitoring over the manipulated variables (in a closed-loop control of pH/DO) to a biological process model would be interesting to explore in the future. It is worth noting that any strategy for bending-points detection might

Table 4
Bending points detection strategies.

Publication	Detection Technique	Variables related to the Bending points	Validation time
Pavšelj et al. (2001)	Derivatives	pH and DO	N/A
Puig et al. (2005)	Minimum Value	OUR	3 months
Poo et al. (2006)	An increase	pH and DO	N/A
Guo et al. (2007)	Derivatives	pH	6 months
Kishida et al. (2008)	Derivatives	pH	185 days
Ga and Ra (2009)	MSC	pH	N/A
Cohen et al. (2003)	ANN classifier	Geometric features from the DO profiles	N/A
Marsili-Libelli (2006)	Pattern recognition based on fuzzy clustering	Filtered derivatives of pH, DO and ORP	5 days
Machón-González and López García (2006)	SOM and K-means	DO, manipulated variable of the DO controller: % air valve opening and temperature	N/A
Marsili-Libelli et al. (2008)	Fuzzy inference system	First derivative of pH and DO profiles, and second derivative of ORP profile	6 months
Luccarini et al. (2010)	ANNs	Identification of "apexes", "knees", and "steps"	3 years
Villez et al. (2010)	Hotelling's statistic	Air flow rate and the derivatives of air flow rate, pH, DO, and ORP	11 days
Kocijan and Hvala (2013)	Gaussian process model	pH, DO, and ORP	N/A
Gu et al. (2012)	MSC	Manipulated variable of the DO controller: Blower frequency	More than 180 days
Antileo et al. (2013)	Constant value and threshold value	Manipulated variables: Carbonate consumption and % air valve opening	220 days
Jaramillo et al. (2018)	Feature extraction and SVM classification	Manipulated variables: Carbonate consumption and % air valve opening	220 days

Validation time: Time in which the proposed bending-points strategies were analyzed/validated.
N/A: Information not available.

be affected in the long-term since during a biological reaction in SBRs the AOB/NOB distribution is time-variant so that the controller parameters must be tuned systematically (Muñoz et al., 2009; Tzoneva, 2007). For these drawbacks, and in order to contribute with more robust advanced monitoring tools, the joint use of feature extraction/selection to obtain adequate indicators that reveal whether an interesting pattern is emerging (Vachtsevanos et al., 2007), along with machine learning tools (e.g., SVMs, ANNs, SOM, among others) Duda et al. (2012), is a very interesting alternative to detect bending points on the manipulated variables curves.

6. Data-driven modeling

Having information about the process evolution available allows plant operators to improve their operating practices, leading to a more stable efficiency over the long-term. This requires having ammonium and nitrate sensors installed in reactors, but these sensors are far from widely available given their high costs, operation sensitivity and complexity in their maintenance. This leads to the motivation of producing software sensors (or soft-sensors) (Haimi et al., 2013) based on online measurements of the secondary variables (pH, DO, ORP) to generate online estimations of ammonium, nitrite and nitrate in the reactor.

On this topic, the contribution of Luccarini et al. (2002) should be considered, where a soft-sensor for estimating NH_4^+ and NO_3^- trends in a pilot-scale SBR was proposed, using the Elman neural network (Elman, 1990) as part of their methodology. Through a software sensor based on both a multiway principal component analysis (MPCA) (Nomikos and MacGregor, 1994) and ANNs, online concentrations of NH_4^+, NO_3^- and PO_4^{3-} using online measurements of pH, ORP and DO as input data were estimated in the work by Hong et al. (2007). In Huang et al. (2009) a soft-sensor based on fuzzy neural networks (FNNs) (Liu and Li, 2004) was designed to estimate NH_4^+, NO_3^- and COD for both the aerobic and anoxic phases using online measurements of pH, ORP and DO as input data as well. Finally, in Huang et al. (2010), a variation of the previous soft-sensor based on a FNN was implemented, with this soft-sensor enabling the estimation of NH_4^+, NO_3^- and PO_4^{3-} in a pilot-scale SBR. A summary of data-driven techniques are shown in Table 5.

The soft-sensor for variable estimation of ammonium, nitrite and nitrate is a powerful tool for online monitoring, and thus relevant information is available to improve the SBR operating policies that can minimize costs and maximize the efficiency of the BNR.

One shortcoming of the soft-sensor review is the lack of emphasis on how the soft-sensor performance is affected after multiple operation cycles of the SBR (long-term). In addition, there are no studies of the process being operated under partial nitrification by using closed-loop control of pH and/or DO; in this case, the soft-sensor should be designed using the manipulated variables of pH and DO as input data.

In other disciplines, such as biological sciences, electrical and mechanical engineering, tools to incorporate uncertainty into the modeling of systems have been applied to acquire greater information about the variables of interest for an adequate prediction of

Table 5
Techniques applied for the development of soft-sensors for nitrogen species.

Publication	Technique	Estimated variables	Validation time
Luccarini et al. (2002)	Elman Neural Network	NH_4^+ and NO_3^-	N/A
Hong et al. (2007)	MPCA and ANN	NH_4^+, NO_3^- and PO_4^{3-}	N/A
Huang et al. (2009)	Fuzzy Neural Network	NH_4^+, NO_3^- and COD	N/A
Huang et al. (2010)	Fuzzy Neural Network	NH_4^+, NO_3^- and PO_4^{3-}	18 months

Validation time: Time in which the proposed soft-sensor were analyzed/validated.
N/A: Information not available.

the model, e.g., expected value, confidence intervals. In particular, Bayesian filters (e.g., Kalman filter and extended Kalman filter (Chui and Chen, 2009) or a particle filter (Arulampalam et al., 2002)) have been widely used to overcome uncertainty problems in dynamic systems (Ching et al., 2006). Future investigations could apply these tools to improve the prediction quality of the models associated with the elimination of ammonia nitrogen in SBRs.

7. Conclusions

In this work, a number of relevant recent studies proposing strategies to improve nitrification in SBRs was reviewed. Bending points is the most widely used strategy to determine aeration length when pH/DO are not closed-loop controlled. However, closed-loop control seems to be more suitable to achieve stable partial nitrification. Future investigations should focus on adequately integrating real time control, artificial intelligence, and activated sludge and data-driven modeling to predict the dynamic behavior of BNR processes and to validate such strategies on a long-term basis by monitoring bacteria population dynamics with molecular tools.

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