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ORIGINAL PAPER

Modified calibration protocol evaluated in a model-based testing of SBR flexibility

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Abstract The purpose of this paper is to refine the BIOMATH calibration protocol for SBR systems, in particular to develop a pragmatic calibration protocol that takes advantage of SBR information-rich data, defines a simulation strategy to obtain proper initial conditions for model calibration and provides statistical evaluation of the calibration outcome. The updated calibration protocol is then evaluated on a case study to obtain a thoroughly validated model for testing the flexibility of an N-removing SBR to adapt the operating conditions to the changing influent wastewater load. The performance of reference operation using fixed phase length and dissolved oxygen set points and two real-time control strategies is compared to find optimal operation under dynamic conditions. The results show that a validated model of high quality is obtained using the updated protocol and that the optimization of the system's performance can be achieved in different manners by implementing the proposed control strategies.

Keywords ASM1 · Calibration · Nitrogen removal · Optimization · Parameter estimation · Real-time control · Respirometry · Sequencing batch reactor · Wastewater treatment

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Introduction

Sequencing batch reactors (SBRs) treatment efficiencies are affected by the influent wastewater characteristics and the design parameters of the reactor (e.g. sludge retention time, volumetric exchange ratio, aeration capacity, SBR cycle time, etc.) [1, 2]. The nature of the SBR technology offers flexibility in operation (more degrees of freedom as compared with conventional systems) and higher degree of automation, two aspects that favor implementation of control strategies for SBR operation [3–6]. As a result, SBRs provide great potential to maintain efficient total nitrogen removal against external disturbances.

There are several approaches to find optimal operation strategies. One of them is the empirical approach, in which the effect of several operational parameters can be tested one-at-a-time (OAT) [7, 8]. This approach is usually expensive, time and resource consuming. Using a model-based approach represents an advantage when defining and evaluating the control strategies, e.g. a detailed map of the operational space can be obtained by performing simulations using cheap computational time and resources [9, 10]. However, the success of this approach depends on the ability of the model to adequately represent the dynamic behavior of the SBR system. The accuracy of model predictions depends on the modeling methodology followed

and advantage should be taken of a good modeling practice protocol. Note that for testing control strategies, the modeling objective and the required model quality are more advanced when compared with other model applications [11]. There are different systematic model calibration protocols available (e.g. BIOMATH, STOWA, WERF, HSG…) and recently a unified protocol has been suggested by the IWA Task Group on Good Modeling Practices (GMP) [12]. Some of the points that have not been addressed in these protocols are the advantage of SBR systems for model calibration, the simulation strategy to obtain proper initial conditions and the statistical evaluation of model calibration and validation results.

The purpose of this paper is to extend the BIOMATH calibration protocol to take advantage of SBR information-rich data during model calibration. The SBR modeling methodology was refined to obtain good quality calibrated models that can provide statistically accurate predictions of ammonium, nitrate and oxygen dynamics in the SBR. The updated protocol is then used to obtain a model for testing the flexibility of SBR operation by applying real-time control strategies (RTCS). The added value of this work is the combination of experimental and modeling work used for verifying an SBR focused calibration protocol, the improvement of a model calibration methodology and the demonstration of the SBR operation flexibility by appropriate controllers.

Methods

Pilot plant

A 30 L SBR was operated treating synthetic wastewater for biological nitrogen removal purposes. In this study, 7 L cycle^{-1} of wastewater were treated in the lab scale SBR using cycles of 8 h divided into reaction (425 min), settling (40 min) and discharge (15 min). A step-feed strategy was applied with four filling events (to better use organic matter for denitrification) and alternating anoxic and aerobic conditions as described in Fig. 1. During aerobic phases, a DO on–off controller was implemented establishing a set point at 2 mgO_2 L^{-1}. Other operating conditions were the volumetric exchange ratio (0.30), the minimum volume (16 L), the hydraulic retention time (1.1 day) and the sludge retention time (15 days) (more details about the pilot plant can be found in Corominas et al. [13]).

Modeling methodology

Using the data acquired in the experimental period, a model for the SBR was obtained by following the BIOMATH protocol [14] presented in Fig. 2. This protocol was refined with some adaptations (elements indicated with an * in Fig. 2) to better address the specific advantages of SBR systems.

The specific advantages of the SBR systems are related to its nature. When calibrating an SBR model, the major advantage is the possibility to observe a large variation in the state variables during one cycle. This variation in a system that alternates aerobic and anoxic phases provides rich information of the nitrification and denitrification processes. Thus, the model calibration applied to SBRs is focused on the calibration at in-cycle level, in which the dynamics of the biological reactions is clearly described by means of analytical measurements or online sensors (e.g. DO). In this sense, it is possible to adjust (if necessary) parameters affecting nitrification and denitrification and also, parameters related to the mass transfer (DO dynamics can be followed when disabling the DO controllers). This calibration is accompanied with a validation based on the daily measurements and, if required, periodic in-cycle evaluation in the middle of the validation period.

The BIOMATH protocol was used and refined during the model building process. In this study, the stages I and II were conducted by strictly following the BIOMATH protocol. Data were acquired for in-cycle calibration, daily validation (50 days) and in-cycle validation (see Fig. 3).

A modification in stage III was included since the influent wastewater characterization was performed using the STOWA protocol [15] which is easier to use in practice and can be conducted with the standard laboratory equipment (stage III, step 7). Following the recommendations of the BIOMATH protocol, lab-scale experimental assays were conducted to determine the long-term behavior parameters, such as Y_{OHO} and b_{OHO} (stage III, step 7) using respirometry [16, 17]. To properly initialize the state variables of the model, the simulation strategy was defined to include the history of the behavior of the SBR (stage IV, steps 8 and 9). Finally, it was proposed to use a statistical evaluation of the fits to have an objective judgment of the calibrated model quality (stage IV, step 11).

General description of the SBR model

Mixing was assumed to be ideal during the aerobic and anoxic phases. The mass transfer coefficient, K_La, was obtained by trial and error until the model and the experimental concentration profiles of DO in the liquid phase matched. This was possible since the DO on–off control was disabled in the cycle after the measurement campaigns, and hence the full re-aeration DO dynamics could be observed. Regarding the settling model, the point settler model was selected since the total solids concentration in the effluent was stable and always below 10 mg L^{-1} as

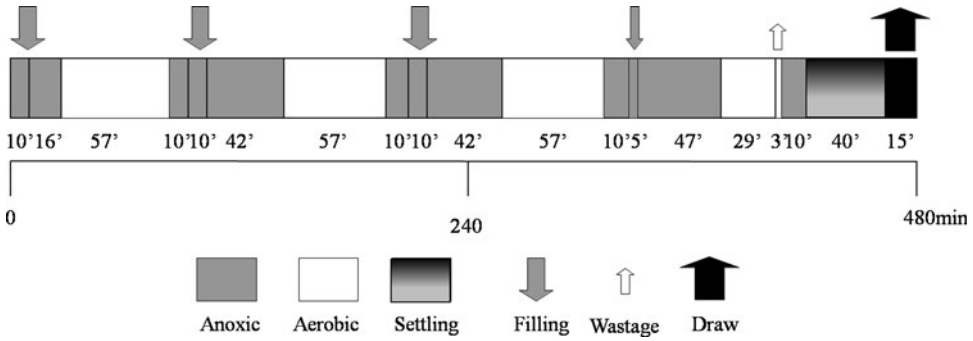

Fig. 1 SBR cycle configuration

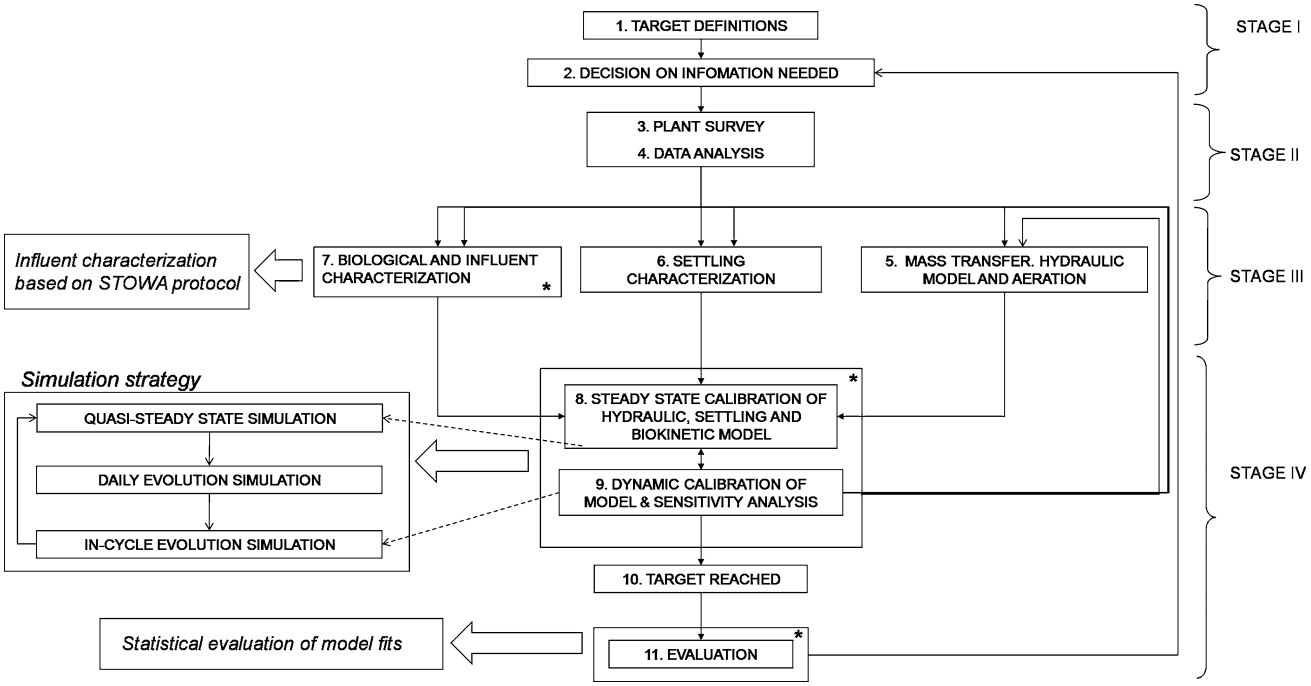

Fig. 2 Adaptation of the BIOMATH calibration protocol (*asterisk* indicates the new contributions to the BIOMATH protocol)

seen in Fig. 3. The biological model ASM1 [18] was used with modifications in both heterotrophic aerobic and anoxic growth rates by considering a monod-type limitation of ammonium as substrate [19]. The effect of temperature on the kinetics was also considered in the model implementation through the Arrhenius equation [20].

Scenario evaluation for controller

Scenario definition

Three scenarios were defined to test the flexibility of the SBR for adapting the operating conditions to the requirements of the influent wastewater load. A reference scenario (fixed cycle configuration and fixed DO set point) was compared with two RTCS that use the OUR (oxygen uptake rate) as a key variable to control the process [21–23].

- *Reference operation*: *Fixed cycle configuration with fixed DO set point*: different values for the DO set points of the aerobic phases were tested (1.0, 1.5, 2.0, 2.5, 3.0 $mgO_2\ L^{-1}$), using the designed fixed cycle configuration. These simulations formed the basis for comparison of the controller performance.
- *Control strategy A*: *Fixed cycle configuration with dynamic DO set point*: A dynamic DO set point control system based on fuzzy logic rules was implemented. The design of the fuzzy controller was based on a

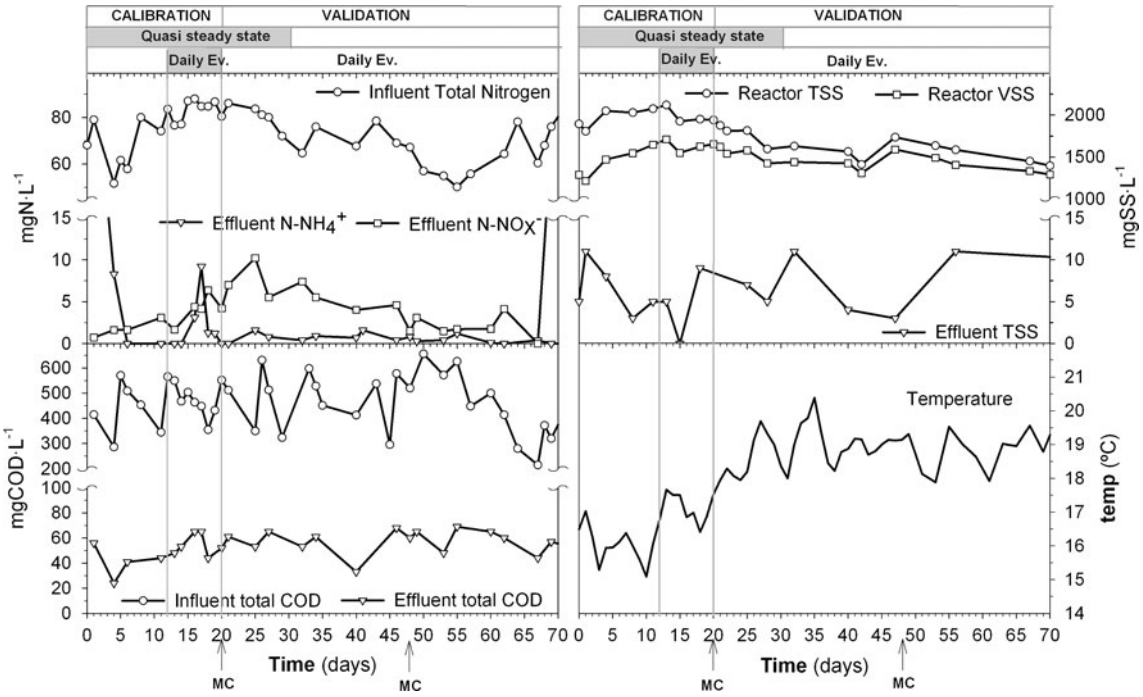

Fig. 3 Evolution of the COD and nitrogen in the influent and effluent (*left*); evolution of total and VSS in the reactor and total suspended solids in the effluent and the temperature of the reactor (*right*)

simple architecture of one input and one output. The input was the OUR_V (the oxygen uptake rate multiplied by the volume, necessary to account for the dilution effects of the SBR when applying a step-feed strategy) at the end of the previous aerobic phase. These values are expressed by means of three fuzzy sets: low, normal, high. The output variable is the percentage of DO set point variation, which was divided into three fuzzy sets (decrease, maintain and increase). The maximum percentage for increase/decrease was 20% of the actual DO set point. The mapping between the inputs (fuzzification) and the outputs (defuzzification) is carried out following the Mandami approach [24].

- *Control strategy B: Dynamic cycle configuration with fixed DO set point*: a real-time control system (RTCS) was implemented to adapt the reaction phase length based on the detection of the ammonia valley (AV) and the nitrate knee (NK) [22]. A threshold for OUR_V data ($OUR_{V,min}$ of 300 $mgO_2\ h^{-1}$) was used to identify the end of the aerobic phases (it was experimentally validated that the AV occurs when achieving this threshold). The end of the anoxic phases was identified when the simulated concentration of oxidized nitrogen was below the threshold ($S_{NOx,min}$) of 0.1 $mgN\ L^{-1}$ (NK appears when nitrate is depleted). A maximum length is established for the reaction phases in case AV or NK are not detected. When the cycle finishes it continues with the next one and therefore, more water can be treated when compared with fixed cycle configuration. This strategy was evaluated for several DO set points between 1 and 3 $mgO_2\ L^{-1}$.

Simulation methodology

Simulations were performed for 50 days with dynamic influent conditions corresponding to the ones occurring during the period for which the model was validated. Several indices (adapted from Copp [25] and presented in Corominas et al. [10]) were calculated to evaluate the different scenarios: the effluent quality (EQ), the aeration energy (AE), the volume of treated wastewater (*Vt*), the effluent concentration limit exceedances for total nitrogen (viol_TN), total suspended solids (viol_TSS), BOD (viol_BOD) and COD (viol_BOD). Moreover, the number of cycles performed was calculated together with the average reduction in length of the aerobic and anoxic phases (for control strategy B).

Results

SBR model calibration: modifications to BIOMATH protocol

Simulation strategy for initialisation

A simulation strategy was defined to properly integrate the history of the system into the biokinetic model calibration

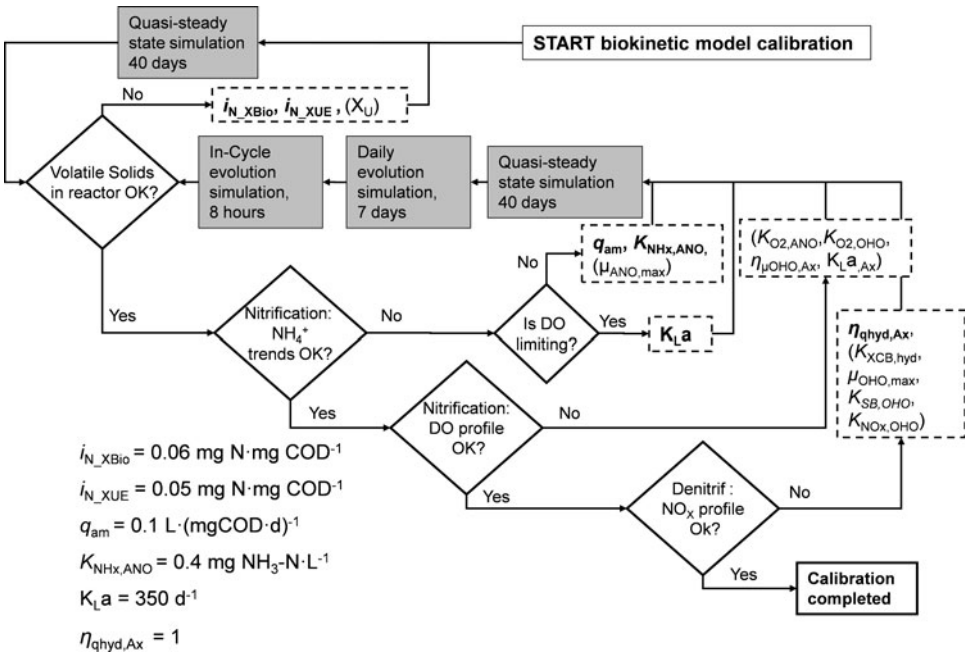

Fig. 4 Stepwise procedure for the model calibration (the parameters between brackets were not adjusted in this study)

(Fig. 2, steps 8 and 9). First, a simulation of 40 days (quasi-steady state; Fig. 2) was performed with averaged influent composition and flows. Within this period, the quasi-steady state (limit cycle behavior) calibration was performed and the long-term behavior parameters were adjusted. Then, a 7-day simulation was run (daily evolution; Fig. 2) applying the dynamics of the influent composition and flow. This daily period permits to properly obtain the initial conditions for the next simulation. Finally, the cycle in which the measurement campaign was conducted was simulated (in-cycle evolution; Fig. 2), and the parameters related to the dynamic behavior were adjusted (in-cycle calibration). Changing any of these parameters implied running the whole simulation procedure again (quasi-steady state + daily evolution + in-cycle evolution).

Calibration results

The quasi-steady state and the in-cycle calibration were conducted following a stepwise procedure (see Fig. 4, refined from Insel et al. [26]). The notation proposed in Corominas et al. [27] is used in this study.

The fine tuning of parameters was performed following a manual trial and error approach based on process engineering knowledge, which is typically done in this field after performing a sensitivity analysis. Alternative to this pragmatic approach often used in practice (STOWA, WERF, HSG, etc.), one could also use more systematic approaches based on the systems analysis as suggested in academic works [28, 29 among others] or a compromise solution as described in Sin et al. [30], which could eventually be used to automate the model calibration and thus to reduce the calibration effort. During the quasi-steady-state calibration, a good match to the measured solids concentration was found using the values obtained experimentally for b_{OHO} (0.3 day^{-1}) and Y_{OHO} (0.67 gCOD gCOD^{-1}) and also the complete influent wastewater characterization using the STOWA protocol. No further calibration of the X_U/XC_B fraction was needed, which forms a strong indication of the good quality of the experimental data and the influent fractionation results. During the in-cycle dynamic calibration, only a few parameters were adjusted (q_{am}, $\eta_{qhyd,Ax}$, $K_{NHx,ANO}$, K_La).

The ASM1 default parameter values were selected as starting point for model calibration. The first parameter (q_{am}) was increased from 0.08 to 0.1 L·(mgCOD day)$^{-1}$ since ammonification is considered a fast process and even this step is omitted in other models (e.g. ASM2d [18]). $\eta_{qhyd,Ax}$ was increased to 1 to increase available substrate for denitrification and therefore better adjust NOx–N profile in the anoxic phases. $K_{NHx,ANO}$ was decreased from 1 to 0.4 mgNH_3–N L^{-1} to lower the limiting effect of ammonia as substrate. K_La was adjusted to (350 day^{-1}) to fit the DO profile as shown in Fig. 5 with the evolution of simulated and experimental DO concentrations. The first cycle on the left corresponds to the measurement campaign cycle working with an on–off controller and on the right the following cycle with the on–off controller disabled. Thus, it can be seen that the dynamics of the simulated dissolved oxygen follow the experimental values closely. The last phases of the cycles correspond to the settling and, therefore, DO data are not reliable there.

In Fig. 4, there is a suggestion of other parameters (between brackets) that can be adjusted during ASM1

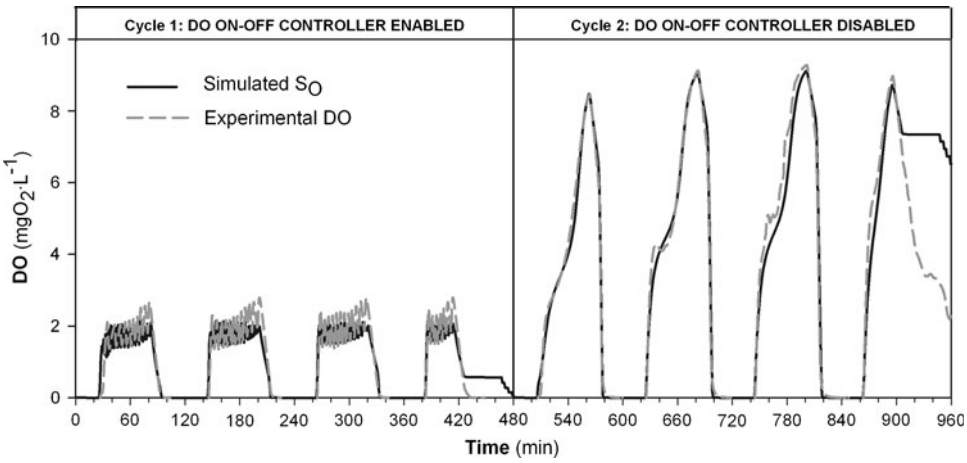

Fig. 5 Simulated versus experimental DO values for the cycle evolution period

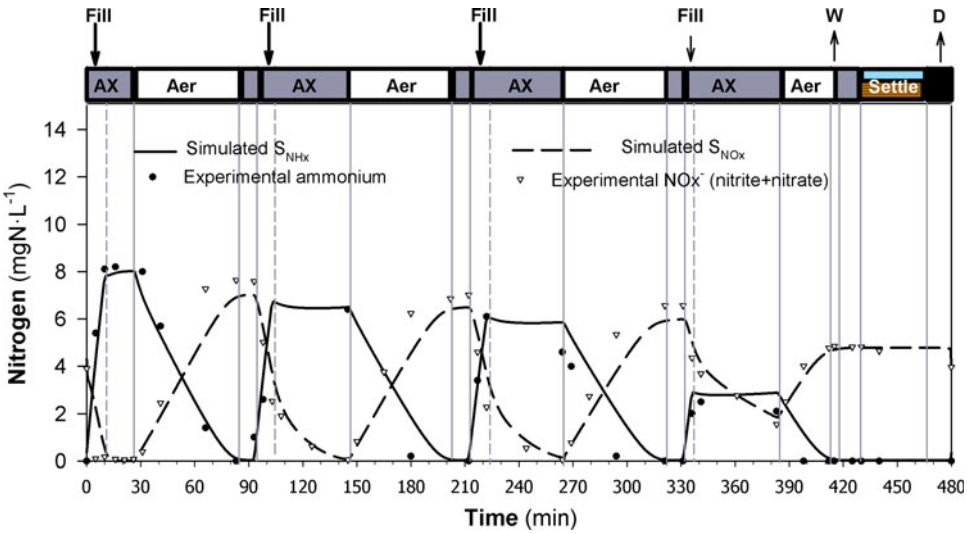

Fig. 6 Simulated versus experimental values for the nitrogen components during the in-cycle evolution period

model calibration. However, the selection of parameters is case specific, and it is recommended to perform a sensitivity analysis prior to model calibration [31]. The results of the experimental and simulated values for nitrogen components are presented in Fig. 6, where a good description of the dynamics can be observed. An even better fit could perhaps be obtained by changing influent nitrogen fractionation and nitrogen-related kinetic parameters.

Validation of the model (stage IV, step 10) was conducted to check whether the target was reached or not. The validation consists of using the calibrated model with a data-set different from the one used in the calibration. The more different the environmental/operating conditions in the validation compared with the calibration period, the stronger the model is. In this validation, the model was run for 50 days applying all operating changes (wastage flow, effluent flow and reactor temperature) and taking into consideration the influent variability (influent composition and influent flow). In this case, the validation was conducted at higher temperatures (from 15 to 20 °C) and with decreased organic load at the end of the validation period (around day 65, see Fig. 3).

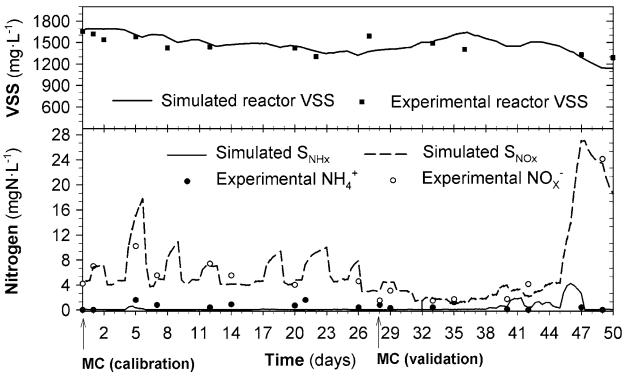

Fig. 7 Results of the daily evolution validation. VSS at the top and nitrogen compounds at the bottom (MC: in-cycle measurement campaign)

No changes in the kinetic, influent fractionation, stoichiometric parameters or the $K_L a$ value were required during this validation which confirms the validity of the calibrated model. The comparison between the simulated and experimental values for the validation period is presented in Fig. 7. It can be seen that the simulated ammonia, nitrate and VSS values match the experimental values, even at the end of the period (days 44–50) when the organic load decreased.

Statistical evaluation of the model fits

The quality of the model fits to the data was evaluated (stage IV, step 11) by performing several statistical tests that included mean error (ME), root mean square error (RMSE), mean absolute error (MAE) and Janus coefficient (J) [32].

$$\mathrm{ME} = \frac{\sum_{n_0}^{n} (y - y')}{n} \quad (1)$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{n_0}^{n} (y - y')^2}{n}} \quad (2)$$

$$\mathrm{MAE} = \frac{\sum_{n_0}^{n} |(y - y')|}{n} \quad (3)$$

$$J^2 = \frac{\mathrm{RMSE}^2_{\mathrm{validation}}}{\mathrm{RMSE}^2_{\mathrm{calibration}}} \quad (4)$$

where y is the observed (real) data, y' the simulated data, and n is the number of evaluated samples.

The results are presented in Table 1 for different periods, i.e. for the in-cycle calibration, the daily validation and the in-cycle validation. The ME stands for the mean error and indicates the predictive bias, which should be ideally close to zero. The model bias for ammonium, nitrate and oxygen predictions are lower in the calibration period as compared to the validation periods (Table 1). These conclusions are supported by MSE and the MAE criteria, which relate to prediction accuracy and should be as small as possible. Accordingly, we find the MSE and MAE criteria to increase in the validation periods. Overall, the lowest bias was found in the ammonium and oxygen predictions (on average 0.7 mgN L^{-1} and 0.5 mgO_2 L^{-1}, respectively), while the oxidized nitrogen prediction bias around 0.9 mgN L^{-1} is also found acceptable (particularly in view of scenario analysis). The Janus coefficient compares the mean squared errors of the predictions in the validation period to the calibration period [31]. A Janus coefficient value close to 1.0 means that the model structure and prediction power is more or less similar in both periods, hence the model is valid (while values much higher than 1.0 imply that the model is invalid). In this study, the Janus coefficient was found close to 1 for the three predicted variables, meaning that the model predictions remain largely valid. Hence, the calibrated model has passed the statistical tests successfully and is ready to be used for evaluation of the controller's performance.

Control strategy evaluation

First of all, the control strategies A and B are analyzed by comparing the observed dynamics during the 50-day simulation period. For strategy B, the specific case of a 2 mgO_2 L^{-1} DO set point is discussed. Later on, indices calculated from the simulations are presented, which allows comparing the full set of scenarios.

Figure 8 shows the variability in the influent (1) and the effluent concentrations (2), the DO set point evolution (3) and the volume of treated wastewater (4) for control strategies A and B. The variability in the influent COD and TKN concentrations (Fig. 8a) strongly influences the effluent S_{NOx} (nitrite + nitrate) concentrations (Fig. 8b). For periods with low COD and high TKN (C/N ratio below 4), the S_{NOx} concentration increases significantly. This becomes an extreme situation at the end of the experimental period with C/N values around 2.6 leading to a S_{NOx} concentration higher than 27 mgN L^{-1} (see days 44–47).

The performance of both strategies was assessed by DO set point evaluation and the volume of treated wastewater. Regarding the DO set point evolution of strategy A (see Fig. 8c), the DO set point fluctuated between 1 and 3 mgO_2 L^{-1} (lower and upper predefined limits) with a mean value of 1.8 ± 0.6 mgO_2 L^{-1}. When compared with the reference scenario at DO set point of 2 mgO_2 L^{-1} similar EQ was obtained (1.35 g pollution/cycle) and AE

Table 1 Evaluation of the model fits using several statistical criteria

	Calibration (in-cycle)			Validation (in-cycle)			Validation (daily evolution)		
	S_{NHx}	S_{NOx}	S_O	S_{NHx}	S_{NOx}	S_O	S_{NHx}	S_{NOx}	VSS
ME	0.23	−0.08	0.11	0.73	0.29	0.36	0.29	−0.27	97.18
RMSE	0.81	0.77	0.87	1.00	0.89	1.01	0.89	1.19	122.89
MAE	0.57	0.55	0.41	0.76	0.59	0.49	0.67	1.63	218.37
J	–	–	–	1.24	1.16	1.16	–	–	–

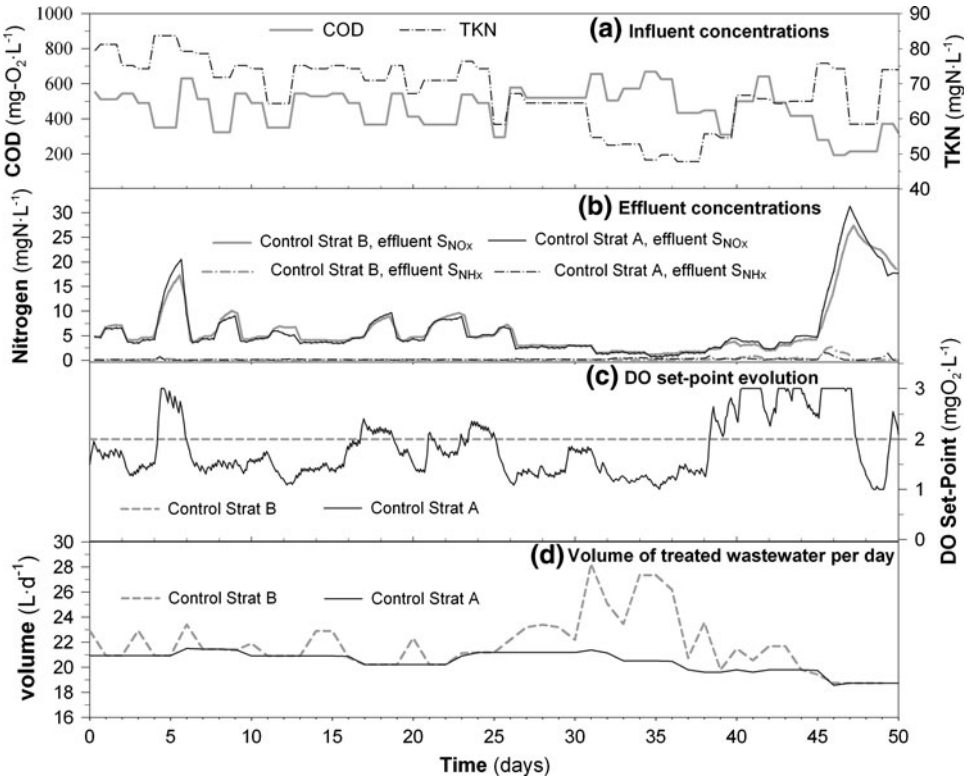

Fig. 8 Comparison of the two control strategies based on the performance of the system (Control Strat A—dynamic DO set point and Control Strat B—dynamic cycle)

Table 2 Performance indices for the simulations (EQ in g cycle^{-1}, AE in kWh cycle^{-1}, Vt in L and concentrations in mg L^{-1})

Scenario	DO set point (mgO_2 L^{-1})										
	1		1.5		2		2.5		3		Dyn
	Ref	CSB	Ref	CSB	Ref	CSB	Ref	CSB	Ref	CSB	CSA
EQ	1.60	1.34	1.33	1.23	1.36	1.30	1.41	1.35	1.45	1.39	1.35
AE	4.53	4.57	4.92	4.89	5.23	5.19	5.54	5.46	5.87	5.80	4.92
Vt	1,025	1,116	1,025	1,094	1,025	1,091	1,025	1,093	1,025	1,098	1,025
viol_TN	16.5	9.8	11.1	8.8	11.2	9.4	11.6	10.6	11.9	11.2	11.2
n° cycles	150	163	150	160	150	159	150	160	150	160	150
↓aerobic	0.0	0.0	0.0	0.7	0.0	2.1	0.0	3.8	0.0	5.5	0.0
↓anoxic	0.0	17.5	0.0	12.8	0.0	10.8	0.0	9.8	0.0	8.8	0.0
Mean X_{BH}	62.2	64.4	65.6	66.5	66.1	67.0	66.3	67.6	66.3	66.6	66.0
Mean X_{BA}	1,527	1,557	1,528	1,563	1,529	1,567	1,528	1,583	1,528	1,556	1,529
Mean S_{NH}	5.1	2.6	1	0.5	0.3	0.2	0.1	0.1	0.1	0.0	0.5
Mean S_{NO}	3.6	4.0	5.5	5.3	6.4	6.1	7.0	6.5	7.4	6.9	6.1

ref reference, *CSA* control strategy A, *CSB* control strategy B, *Dyn* dynamic set point

decreased from 5.23 to 4.92 kWh cycle^{-1} (see Table 2). Introducing a dynamic set point improves denitrification efficiency and saves energy during low-loaded conditions. Looking at the volume of treated wastewater per day (Fig. 8d), the average volumes treated using the control strategy A and B were 20.5 and 21.8 L day^{-1}, respectively.

The dynamics of the process permit to compare both strategies when facing different influent characteristics. When the C/N ratio in the influent is higher than 7, both strategies optimize the performance. Control strategy A reduces the aeration energy, whereas control strategy B increases the plant capacity because the reaction time can be reduced, especially from days 30–38. When the C/N

ratio is low (e.g. days 44–47), the dynamic DO set point strategy increases the DO set point until 3 mg L^{-1} with corresponding ammonium depletion and nitrate production.

Table 2 presents the calculated performance indices for the full set of simulated scenarios with control strategies A and B. In addition, several fixed DO set points were evaluated for the aerobic phases (from 1 to 3 mgO_2 L^{-1}) in the reference case and also for the control strategy B.

Regarding the simulation results of reference operation (Table 2), the increase in the DO set points caused an AE increment from 4.53 to 5.87 kWh $cycle^{-1}$. The optimum EQ value (1.33 g pollution units·$cycle^{-1}$) for a fixed DO set point was achieved at 1.5 mgO_2 L^{-1}. The nitrogen effluent exceedance index (viol_TN) reached the lowest value when working at 1.5 mgO_2 L^{-1}. There were no violations for TSS, BOD and COD in any case (results not shown). Therefore, the best operation for reference operation would be using a DO set point of 1.5 mgO_2 L^{-1}.

When implementing the control strategy B for adjusting the length of the reaction phases, the number of completed cycles increased around 7% and, proportionally, the treated influent flow (note that the volume of wastewater treated per day in control strategy A is variable due to influent pump instabilities during the experimental period. The same flow values were considered for control strategy B simulations). This is possible because the reaction time is adjusted and under favorable conditions (e.g. with high C/N ratio and low influent TKN) the cycle length can be shortened. The reduction in anoxic phases was between 8.8 and 17.5% and the reduction in aerobic phases between 0.0 and 5.5%. The higher the selected DO set point, the higher the aerobic length reduction is and the lower the anoxic length reduction. This is true in the cases where the minimum SRT for nitrification is ensured. The establishment of a minimum length for the aerobic phases is to make sure that the aerobic SRT is sufficient to keep the nitrifiers in the system. In addition, the optimum DO set point was 1.5 mgO_2 L^{-1}.

When comparing reference operation with control strategy B, the results showed that EQ and viol_TN decreased using control strategy B. The major improvement occurred when using the DO set point of 1 mgO_2 L^{-1}, where the number of violations decreases by 40% and the anoxic phase length is reduced by 17.5%. This coincides with short periods for the nitrifiers under famine conditions combined with an increase in the biomass production, which improves the performance of the system.

Finally, the control strategy A simulations (dynamic DO set point with fixed cycle configuration) resulted in a performance similar to the one obtained with the reference operation with DO set point between 1.5 and 2 mgO_2 L^{-1}. This is explained by the mean DO set point of 1.8 mgO_2 L^{-1} obtained with this strategy.

As a summary, it was found that both presented strategies were useful, but different benefits were obtained. The plant manager is the responsible to select the operating strategy. This decision can be based on the influent wastewater characteristics. For low/normal loads, it would be preferable to operate with a dynamic DO set point (control strategy A) maintaining the fixed length of the phases (optimizing the aeration energy, but avoiding famine conditions for the microorganisms in the idle phase if control strategy B would be applied). For higher loads, it would be interesting to use control strategy B for increasing the plant capacity. Finally, a combined strategy could be applied when a higher plant capacity would be needed together with a higher aerobic reaction time (since control strategy B is able to shorten the length of the phases, but not to increase it beyond a maximum length).

Conclusions

A refined model calibration methodology was developed for SBR systems, which has interesting characteristics facilitating data collection and parameter estimation. The main updates as compared with the BIOMATH protocol were:

- The definition of a simulation strategy permitting to take into consideration the history of the plant's operating conditions for the model calibration.
- A suggested scheme for stepwise estimation of parameters that are especially influencing important process state variables.
- The evaluation of the obtained validated SBR model using statistical criteria to ensure an objective judgment of the quality of the fits and especially validity (Janus coefficient).

This protocol was applied to obtain a thoroughly validated model which was subsequently used to show that control strategies can improve and optimize the SBRs performance.

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