Title
Calibration of the comprehensive NDHA-N₂O dynamics model for nitrifier-enriched biomass
using targeted respirometric assays.

Author list
Carlos Domingo-Félez\textsuperscript{a}, María Calderó-Pascual\textsuperscript{a}, Gürkan Sin\textsuperscript{b}, Benedek G. Plósz\textsuperscript{b,1}, Barth F. Smets*\textsuperscript{a}

\textsuperscript{a}Department of Environmental Engineering, Technical University of Denmark, Miljøvej 115, 2800 Kgs. Lyngby, Denmark

\textsuperscript{b}Department of Chemical and Biochemical Engineering, Technical University of Denmark, Søltofts Plads 227, 2800 Kgs. Lyngby, Denmark

\textsuperscript{1}Present address: Department of Chemical Engineering, University of Bath, Bath, England.

* Corresponding author:
Barth F. Smets, Phone: +45 4525 1600, Fax: +45 4593 2850, E-mail: bfsm@env.dtu.dk
Abstract

The NDHA model comprehensively describes nitrous oxide (N2O) producing pathways by both autotrophic ammonium oxidizing and heterotrophic bacteria. The model was calibrated via a set of targeted extant respirometric assays using enriched nitrifying biomass from a lab-scale reactor. Biomass response to ammonium, hydroxylamine, nitrite and N2O additions under aerobic and anaerobic conditions were tracked with continuous measurement of dissolved oxygen (DO) and N2O.

The sequential addition of substrate pulses allowed the isolation of oxygen-consuming processes. The parameters to be estimated were determined by the information content of the datasets using identifiability analysis. Dynamic DO profiles were used to calibrate five parameters corresponding to endogenous, nitrite oxidation and ammonium oxidation processes. The subsequent N2O calibration was not significantly affected by the uncertainty propagated from the DO calibration because of the high accuracy of the estimates. Five parameters describing the individual contribution of three biological N2O pathways were estimated accurately (variance/mean < 10% for all estimated parameters).

The NDHA model response was evaluated with statistical metrics (F-test, autocorrelation function). The 95% confidence intervals of DO and N2O predictions based on the uncertainty obtained during calibration are studied for the first time. The measured data fall within the 95% confidence interval of the predictions, indicating a good model description. Overall, accurate parameter estimation and identifiability analysis of ammonium removal significantly decreases the uncertainty propagated to N2O production, which is expected to benefit N2O model discrimination studies and reliable full scale applications.

Keywords: Nitrous oxide, Respirometry, Uncertainty, Modelling, Parameter Estimation
1. Introduction

Nitrous oxide (N$_2$O) is a greenhouse gas emitted during biological nitrogen removal (BNR). The carbon footprint of wastewater treatment plants (WWTPs) is highly sensitive to N$_2$O emissions (Gustavsson and Tumlin, 2013), thus reducing N$_2$O emissions is beneficial for the energy balance of WWTPs.

During BNR operations biological and abiotic pathways are responsible of N$_2$O emissions (Schreiber et al., 2012). Ammonia-oxidizing bacteria (AOB) produce N$_2$O during incomplete ammonium (NH$_4^+$) oxidation to nitrite (NO$_2^-$) (nitrifier nitrification, NN). Under low dissolved oxygen (DO) AOBs use NO$_2^-$ as the terminal electron acceptor and also release N$_2$O (nitrifier denitrification, ND). Heterotrophic denitrification is a 4-step process where N$_2$O is an obligate intermediate. Under low carbon-to-nitrogen ratios or in the presence of DO heterotrophic denitrification is not complete and N$_2$O can be released (HD) (Richardson et al., 2009). Hydroxylamine (NH$_2$OH) and free nitrous acid (HNO$_2$) are intermediates of NH$_4^+$ oxidation which can produce N$_2$O abiotically.

Process models are useful tools that translate our understanding of N$_2$O production into mathematical equations. N$_2$O model structures vary depending on the number of pathways, nitrogenous variables or parameters considered (Ding et al., 2016; Ni et al., 2014; Pocquet et al., 2016). The description of the autotrophic contribution transitioned form single- (NN or ND) to two-pathway (NN and ND) models to capture the N$_2$O dynamics observed during N-removal (Pocquet et al., 2016; Schreiber et al., 2009). Recently, a consilient N$_2$O model was proposed (NDHA, Nitrifier nitrification, nitrifier Denitrification, Heterotrophic denitrification and Abiotic) that predict three biological pathways and abiotic processes (Domingo-Félez and Smets, 2016). Potentially, the NDHA model describes N$_2$O production under a wide range of operational conditions.

N$_2$O models are extensions of existing structures describing nitrogen removal and thus, calibration of N$_2$O dynamics also requires accurate predictions of the primary substrates (i.e. DO, NH$_4^+$, NO$_2^-$).
The experimental datasets used for calibration in lab-scale systems are either directly obtained from the reactor performance (Ding et al., 2016) or by conducting batch experiments (Ni et al., 2011). Initially, the information content of the experimental design was not studied because models aimed at describing N$_2$O trends without focusing on rigorous calibrations (Law et al., 2011). However, the amount and quality of data of the experimental design directly impact the calibration results (Dochain and Vanrolleghem, 2001).

Some studies report the proposed calibration framework (Guo and Vanrolleghem, 2014), but the N$_2$O parameter estimation procedures are often ill-described, with little information about each step. For example, the parameter subset selection considered during parameter estimation is sometimes not addressed. Local sensitivity measures are used as rankings for parameter selection (Pocquet et al., 2016; Spérandio et al., 2016), but these rankings are dependent on the initial parameter values and do not capture parameter interactions (Brun et al., 2001).

The overall fit and capabilities to describe N$_2$O dynamics has relied on analysis from best-fit simulations (e.g. R$^2$), which can lead to ambiguous results that cannot discriminate between models (Lang et al., 2017; Pan et al., 2015). A more rigorous analysis of residuals (e.g. Gaussian distributions, autocorrelation functions (ACF), F-test, etc.) would benefit the validation of the model response (Bennett et al., 2013).

Also, addressing the practical identifiability of newly estimated parameters will improve N$_2$O model discriminations procedures. For example, the parameter variance and correlation matrix are indicators of the confidence that can be given to a value, but they are not always reported, which makes it difficult to compare between N$_2$O model predictions (Ding et al., 2016; Kim et al., 2017; Pocquet et al., 2016; Spérandio et al., 2016). Practical identifiability problems might contribute to the large variability of parameter values in N$_2$O models (Domingo-Félez et al., 2017).

The uncertainty obtained during calibration translates into confidence intervals for model predictions. The accuracy, or width of the confidence interval, associated to the N$_2$O emissions
will be a key factor to consider during the development of mitigation strategies. Yet, the uncertainty of N₂O emissions associated to model calibration is not studied.

The objective of this study is to demonstrate and evaluate a standardized procedure for parameter estimation from N₂O models that relies on respirometric assays and in particular its application to analyse and validate the recently developed NDHA models. These assays are designed to allow the sequential fit of model components. The novelty resides in improving N₂O calibration procedures by targeting sources of uncertainty. Subsequently, the calibration results and associated uncertainty are evaluated. The calibration approach presented is a rigorous tool beneficial for N₂O model discrimination.
2. Material and Methods

2.1. Experimental Design

Nitrifying enrichment culture.

A lab-scale nitrifying sequencing batch reactor (5 L) was operated and displayed stable performance for three months after enrichment from an AS mixed liquor sample. Synthetic wastewater (modified after Graaf et al., 1996) with NH$_4^+$ as the only nutrient was fed at 0.5 g NH$_4^+$-N/L·d and a constant aeration rate maintained oxygen-limited conditions (DO below 0.25 mg/L) (SI-S1). NH$_4^+$ removal was 82 ± 14%, and nitritation efficiency (NO$_2^-$/NH$_4^+$ removed) at 85 ± 24% (Su et al., 2017). The biomass composition, based on 16 rRNA targeted qPCR analysis had a dominance of AOB over NOB (30:1). Detailed information of the qPCR analysis can be found in (Terada et al., 2010).

Monitoring nitrification and N$_2$O production via extant respirometric assays.

Biomass samples were harvested towards the end of the react cycle by centrifugation at 3600 g for 5 min, washed and resuspended in nitrogen-free mineral medium three times to eliminate any soluble substrate.

Assays were performed in parallel at 25°C in two 400-mL jacketed glass vessels completely filled with biomass and sealed with the insertion of a Clark-type polarographic DO electrode (YSI Model 5331, Yellow Springs, OH). Biomass samples were saturated with air or pure oxygen prior to the initiation of the respirometric assays. A decrease in the DO level in the vessel due to substrate oxidation was measured by the DO probe and continuously acquired by a personal computer interfaced to a DO monitor (YSI Model 5300, Yellow Springs, OH) by a multi-channel data acquisition device (LabPC+, National Instruments, Austin, TX). DO profiles were acquired at a user-defined frequency below the response time of the sensor (0.2 Hz). Liquid N$_2$O concentrations were measured with Clark-type microsensors (N2O-R, Unisense A/S, Aarhus, Denmark) and pH (WTW GmbH, Weilheim, Germany). Stock solutions for all the reagents were
prepared from high-purity chemicals for \( \text{NH}_4\text{HCO}_3, \text{NH}_2\text{OH}\cdot\text{HCl}, \text{NaNO}_3, \text{C}_3\text{H}_5\text{NaO}_2 \) (Sigma Aldrich) and by sparging \( \geq 99.998\% \) gas in deionized water for \( \text{N}_2\text{O} \) (Sigma-Aldrich). Photometric test kits were used to analyze N-substrates (1.14752, 1.09713, 1.14776, Merck KGaA, Darmstadt, Germany).

[Table 1]

**Experimental Design**

The aim of the experimental design was to obtain informative data on \( \text{N}_2\text{O} \) dynamics for a nitrifier dominated biomass to allow estimation of parameters of the NDHA model, which captures processes associated with nitrification, denitrification, and abiotic processes. Respirometric approaches were exclusively taken (on-line, high-rate \( \text{O}_2 \) and \( \text{N}_2\text{O} \) measurements) as they allow accurate parameter estimates compared to substrate depletion experiments (Chandran et al., 2008). The kinetics of the oxidation of the primary N-substrates (\( \text{NH}_4^+, \text{NH}_2\text{OH} \) and \( \text{NO}_2^- \)) were individually and step-wise, measured via extant respirometry under various initial DO conditions, with continuous \( \text{N}_2\text{O} \) measurements (Table 1). Then the interaction between the different N species was ascertained by liquid sampling at the end of certain experiments. In addition, specific experiments were conducted to measure the heterotrophic and abiotic contributions to total \( \text{N}_2\text{O} \) production during nitrification. Biomass content (MLSS, MLVSS) was measured in duplicates according to APHA (APHA et al., 1999).

The purpose was to predict the fate of the primary N-substrates based on the specific oxygen-consuming rate. By sequentially adding substrate pulses from oxidized to reduced form (\( \text{NO}_2^- \rightarrow \text{NH}_2\text{OH} \rightarrow \text{NH}_4^+ \)), the individual rates can be isolated (Brouwer et al., 1998). The \( \text{N}_2\text{O} \) dynamics from \( \text{NH}_4^+ \) removal at varying \( \text{NO}_2^- \) and DO concentrations can be investigated simultaneously.

**Scenarios (Batches grouped by substrate added: \( \text{NH}_4^+, \text{NH}_2\text{OH}, \text{NO}_2^- \))**

A scenario (e.g. Scen_AMO) was defined as a group of experiments with the same primary N-substrate added by pulses (Table 1). The overall oxygen consumption was the additive effect of
several independent oxygen consumption processes, potentially including endogenous -, $\text{NO}_2^-$, $\text{NH}_2\text{OH}$ -, and $\text{NH}_4^+$-respiration.

2.2. $\text{N}_2\text{O}$ model description: NDHA

The NDHA model was proposed as a consilient model to describe $\text{N}_2\text{O}$ dynamics under a variety of conditions for biomass containing both autotrophic and heterotrophic fractions (Domingo-Félez and Smets, 2016). It considers $\text{N}_2\text{O}$ production from two autotrophic and one heterotrophic biological pathways, plus abiotic $\text{N}_2\text{O}$ formation based on recent findings (Soler-Jofra et al., 2016). Unlike any other model, NDHA can qualitatively capture NO and $\text{N}_2\text{O}$ profiles that have observed at high and low DO (Castro-Barros et al., 2016; Kampschreur et al., 2008; Rodriguez-Caballero and Pijuan, 2013; Yu et al., 2010). Here we aim to calibrate the NDHA model.

The following summarizes the essential and unique components of NDHA; for more information see (Domingo-Félez and Smets, 2016). The two autotrophic pathways have two different NO-producing processes, which are combined into a single $\text{N}_2\text{O}$-producing process. In Nitrifier Nitrification (NN), NO$_{\text{NN}}$ is produced during $\text{NH}_4^+$ oxidation (AOR) under oxic conditions. Higher AOR will likely increase NO$_{\text{NN}}$ and also $\text{N}_2\text{O}$. A fraction of NH$_4^+$, proportional to AOR is always released as $\text{N}_2\text{O}$$_{\text{NN}}$. In autotrophic denitrification (ND), under low DO NO$_{\text{ND}}$ is produced by the reduction of HNO$_2$ with $\text{NH}_2\text{OH}$. This step is negatively affected by DO. The reduction of both NO$_{\text{ND}}$ and NO$_{\text{NN}}$ is lumped in one process with no oxygen inhibition as it is not known whether both NIR and NOR steps are directly inhibited by DO (Kozlowski et al., 2014). Thus, if NIR is inhibited by DO the overall ND-associated $\text{N}_2\text{O}$ production will be indirectly limited. The 4-step denitrification model was considered based on (Hiatt and Grady, 2008). Individual process rates and inhibition/substrate coefficients were used as suggested for systems with low substrate accumulation. Nitrification produces HNO$_2$ and $\text{NH}_2\text{OH}$. Abiotically $\text{NH}_2\text{OH}$ can form HNO which dimerizes via $\text{H}_2\text{N}_2\text{O}_2$ to $\text{N}_2\text{O}$ and $\text{H}_2\text{O}$ (Eq. i). HNO accumulation could occur due to an imbalance between the two reactions, leading to chemical $\text{N}_2\text{O}$ production (Igarashi et al., 1997).
Nitrosation of NH₂OH (Eq. ii) has also been postulated as a relevant reaction in partial nitrification reactors (Soler-Jofra et al., 2016).

\[
\text{NH}_2\text{OH} \rightarrow \text{HNO} \rightarrow \text{H}_2\text{N}_2\text{O}_2 \rightarrow \text{N}_2\text{O} + \text{H}_2\text{O} \quad (\text{Eq. i})
\]

\[
\text{NH}_2\text{OH} + \text{HNO}_2 \rightarrow \text{N}_2\text{O} + \text{H}_2\text{O} \quad (\text{Eq. ii})
\]

The pH data was used as input to the model to calculate the corresponding NH₃ and HNO₂ concentrations.

### 2.3. Parameter estimation procedure

The steps in the parameter estimation procedure were to (1) estimate the best fit parameters to describe O₂ consumption and N₂O production during the various (or during each type of) experimental scenarios (Figure 1), (2) estimate the contribution of separate pathways to the total N₂O production, and (3) quantify the uncertainty of model predictions.

#### 2.3.1. Parameter subset selection - Global sensitivity analysis

A global sensitivity analysis (GSA) was performed to identify the parameters most determinant of model outputs by linear regression of Monte-Carlo simulations (Sin et al., 2009). Uncertainty from model parameters was propagated as 10-25-50% uniform variations from their default value to model outputs. Latin hypercube sampling was used to cover the parameter space. The Standardized Regression Coefficient method was used to calculate the sensitivity measure βₖ, which indicates the effect of the parameter on the corresponding model output (Campolongo and Saltelli, 1997) (convergence found with 500 samples). The duration of every experiment was discretized in 400 parts and the GSA run at each point (SI-S2).

Parameters describing the elemental biomass composition (e.g. iNXB), yield and temperature coefficients were fixed at default values and not considered for calibration. For each scenario the top ranked most sensitive parameters were preliminary selected as candidates for parameter estimation. All possible combinations of parameter candidates were assessed by increasing the
size of the calibration subset to find the largest identifiable subset with the lowest error, assessed by the Akaike Information Criterion (AIC) (Akaike, 1974). To compare the information content of different parameter subsets of the same size the optimal experimental design criteria modE (Dochain and Vanrolleghem, 2001) was calculated together with RDE (Ratio of normalized D to modified E criteria), which captures the accuracy and precision of a calibrated subset (Machado et al., 2009). Newly estimated parameters were fixed at their best-fit estimate on the next calibration step (Figure 1).

2.3.2. Error minimization

The error function for problem minimization was defined as:

\[
\text{Error} = \sum_{j}^{m} \frac{1}{n} \sum_{i}^{n} \left( \frac{y_{\text{sim},i} - y_{\text{obs},i}}{\sigma_{i}} \right)^2
\]

Where \( m \) is the number of experiments in one scenario (e.g. 2 NOB experiments in Scen_NOB), \( n \) the number of experimental points of each experiment, \( y_{\text{sim},i} \) the model prediction and \( y_{\text{obs},i} \) the experimental data at time \( i \), and \( \sigma_{i} \) the standard error of the experimental data. The minimization problem was started with global search method over a wide parameter space (GlobalSearch algorithm). From the estimated minimum, multiple local searches (PatternSearch algorithm) were started randomly in a narrower parameter space to avoid local minima. Model simulations were performed in the Matlab environment (The Mathworks Inc., Natick, USA).

2.3.3. Validation of model response and parameter estimates

To test the validity of the model response (i.e. the adequacy of model to predict the observed data points) the residuals \( (y_{\text{sim},i} - y_{\text{obs},i}) \) were compared to a Gaussian distribution with a one-sample Kolmogorov-Smirnov test (Lilliefors, 1967). Interdependency of residuals was analysed by autocorrelation for different lag times (Cierkens et al., 2012). The quality of the model fit was calculated via correlation coefficients (\( R^2 \)) and challenging the hypothesis of the linear regression with simultaneous unit slope and zero intercept, where a value of 0/1 indicates a bad/good model fit (F-test). Moreover, by separating the error into three components: means, slope differences
and randomness the Mean Squared Error Prediction (MSEP) index identifies the main error source between randomness, mean and standard deviation of residuals (NC, ME, SE) (Haefner, 2005). The prediction accuracy and the validation of the model to individual experiments was evaluated by the Root Mean Squared Error (RMSE) and the Janus coefficient to compare the RMSE between model calibration and validation (Power, 1993).

Based on the Fisher Information Matrix (FIM) collinearity indices were calculated to evaluate the identifiability of parameter estimates (Brun et al., 2001). Approximate confidence regions were calculated following $J_{\text{crit}} = J_{\text{opt}} \left(1 + \frac{p}{N_{\text{data}} - p} F_{a,p,\nu} \right)$ (Beale, 1960). Coefficients of variation (CV) were described as the ration between the variance ($\sigma$) and the mean ($\mu$) of the estimate.

The reliability of predictive distributions (95% confidence intervals) was evaluated by calculating the Percentage of observations within the Unit Confidence Interval (PUCI) (Li et al., 2011), which combines the fraction of experimental points inside the confidence interval (PCI) and the Average Relative Interval Length (ARIL). $\text{ARIL}_{0.95} = \frac{\text{Limit}_{\text{Upper},0.95} - \text{Limit}_{\text{Lower},0.95}}{\text{Data}}$ (Jin et al., 2010). A smaller ARIL value (narrow distance between upper and lower 95% CI predictions) and a larger PUCI represent a better performance.

### 2.4. Uncertainty evaluation

The effect of directly estimated versus assumed parameter uncertainty was evaluated by Monte-Carlo simulations. The parameter distribution was sampled via LHS ($n = 500$) for two cases: from the distributions obtained during calibration, and compared to uncertainty classes assumed from literature as a reference case (Sin et al., 2009). The resolution of prediction uncertainty was assessed by the ARIL.
3. Results

3.1. Oxygen consumption during respirometric assays.

Each scenario grouped experiments based on the substrate added: NO$_3^-$ (Scen_NOB) NH$_2$OH (Scen_HAO) or NH$_4^+$ (Scen_AMO). In all scenarios, even prior to any substrate spikes, oxygen consumption was always positive and proportional to the biomass concentration due to endogenous respiration. After substrate addition, oxygen consumption increased, to a much higher rate with NH$_4^+$ or NH$_2$OH than with NO$_3^-$ spikes (Figure 2). The lower NO$_3^-$ oxidizing rate of the biomass agreed with the measured low NOB vs AOB abundance (ca. 1:30). pH was not controlled and varied between 7 and 8, decreasing during NH$_4^+$ oxidation and increasing during reaeration periods due to CO$_2$ stripping or by manual base addition (NaOH).

The ranking from the averaged GSA for DO shows that the sequential scenarios (measuring the respirometric response to addition of synthetic substrates) provides sufficient information to individually estimate the relevant biokinetic parameters of each step in the ammonium oxidation process (Figure 3). For example, in Scen_NOB the maximum growth rate for NOB ($\mu_{\text{NOB}}$) ranked first, while in Scen_AMO the substrate affinity ($K_{\text{AOB.NH}_3}$) and maximum growth rate for the AMO ($\mu_{\text{AOB.AMO}}$) step ranked in the top.

3.1.1. Estimation of primary substrate kinetics based on DO profiles

Initial conditions for each batch were defined by simulating endogenous decay and hydrolysis with default parameters. The objective of the parameter subset selection was to calibrate the minimum number of identifiable parameters that explain the data. A total of five parameters could be estimated from the aerobic scenarios (Table 2). The calibrated parameters for Scen_NOB were $\mu_{\text{NOB}}$ and $k_H$, for Scen_AMO $\mu_{\text{AMO}}$ and $K_{\text{AOB.NH}_3}$, and for Scen_AMO_DO $K_{\text{AOB.O}_2\text{AMO}}$ (Table 2). To illustrate the procedure used for every scenario results from Scen_NOB and Scen_AMO are
summarized in the SI (SI-S3). The electron distribution in AOB differs between NH$_4^+$ (Scen_AMO) oxidation and isolated NH$_2$OH oxidation (Scen_HAO) (SI–S4). Hence, parameter estimation results from Scen_HAO were not considered representative of NH$_4^+$ oxidation, our targeted process. To describe more accurately the low NH$_2$OH concentration values reported in literature (Soler-Jofra et al., 2016) the affinity for NH$_2$OH, $K_{AOB,\text{NH}_2\text{OH}}$, was increased compared to other N$_2$O models (SI–S4). The oxygen consumption rate of NH$_4^+$ experiments drops quickly to endogenous levels (Figure 2, C). The lack of an intermediate oxygen uptake rate indicates that no significant accumulation of an intermediate which agrees with the proposed higher affinity for NH$_2$OH (2.29 mgCOD/mgN). [Table 2]

Validation of model response (DO) and primary N-substrate parameter estimates

The model consistently described the experimental DO profiles for every scenario (F-test = 1, which indicates that we fail to reject the null hypothesis of slope 1 and intercept 0 between simulations and observations) (Figure 4, A, B). The MSEP indicated that randomness was the main source of error compared to the mean or standard deviation, validating the model response during calibration (NC > ME, SE, SI-S5). The uncertainty of the parameter estimates (Table 2) was propagated to the model predictions, showing an increased resolution of the 95% predictive distributions for DO compared to the uncertainty of the reference case (ARIL = 3.8/0.5 before/after parameter estimation). The PUCI (percentage of observations bracketed by the unit confidence interval) also improved from 0.4 to 1.5.

Best-fit parameter estimates at each scenario were estimated at high accuracy: coefficients of variation (CV) were below 7% for all cases (Table 2) and the collinearity indices below 15, as suggested for identifiable subsets (Brun et al., 2002) (SI-S3). The high correlation between $\mu_{\text{AOB,AMO}}$ and $K_{\text{AOB,NH}_3}$ typically occurs for Monod-type kinetics but it did not affect their identifiability.

While the error distribution of each scenario was not normally distributed (Kolmogorov-Smirnov test 95%), no systematic deviations were observed (Figure 4). The analysis of the residuals
indicated that for scenarios AMO and NOB the errors were autocorrelated (SI-S5). Subsequently, the effect of sampling resolution on the optimal parameter values and uncertainties was minimized until the autocorrelation obtained was negligible (SI-S5). As the sampling data frequency decreased through subsampling, the accuracy of estimates decreased too (e.g. \(CV_{\text{AMO}} = 2\%\) point/2 min, 4.4% point/10min). However, the lower precision of the best-fit estimates did not translate into higher simulation uncertainty for the primary N-substrates (\(\sigma_{95\%CI}\) increased by less than 0.06 mg/L for DO, \(\text{NH}_4^+\), \(\text{NH}_2\text{OH}\) or \(\text{NO}_2^-\)). Consequently, while the autocorrelation of residuals affected the DO parameter estimation results it did not impact the \(\text{N}_2\text{O}\) calibration, the focus of this study.

The fitted model was evaluated on five additional experiments not used during calibration with varying initial pH (7-8), \(\text{NO}_2^-\) (0-6.2mgN/L) and \(\text{NH}_4^+\) pulses (1-10mgN/L). The Janus coefficient and \(R^2\) were close to unity (1.24 and 0.997) indicating a good model validation (Figure 4, C, D).

In sum, the respirometric experimental design can be used to precisely identify and calibrate the primary substrate dynamics of the NDHA model based on the DO profiles.

### 3.2. Dynamics of \(\text{N}_2\text{O}\) during different scenarios

In the same scenarios considered for DO calibration liquid \(\text{N}_2\text{O}\) was also continuously measured (Figure 2). Moreover, the role of the primary N-substrates (\(\text{NH}_4^+\), \(\text{NH}_2\text{OH}\), \(\text{NO}_2^-\), and \(\text{NO}_3^-\)) on \(\text{N}_2\text{O}\) production was also studied under anoxic conditions (Table 1). Under conditions heterotrophic denitrification (Scen_An_HB) the presence of \(\text{NO}_2^-\) and \(\text{NO}_3^-\) did not show any net \(\text{N}_2\text{O}\) production (data not shown). However, \(\text{N}_2\text{O}\) was consumed after sCOD addition when no other N-substrate was present, indicating a positive HD contribution to the total \(\text{N}_2\text{O}\) pool (Figure 5). During \(\text{NO}_2^-\) oxidation experiments or at the onset of anoxia in the presence of \(\text{NO}_2^-\) and \(\text{NO}_3^-\) no \(\text{N}_2\text{O}\) production was detected (Figure 2, A).
AOB-driven NH$_4^+$ oxidation (Scen_AMO) produced a small amount of N$_2$O under aerobic conditions and significantly increased at the onset of anoxia (Figure 2). The specific N$_2$O production rate (mgN$_2$O-N/gVSS.min) obtained in duplicate experiments – carried out at varying biomass concentrations – were in close agreement, thus indicating biologically-driven N$_2$O production (SI-S6).

The role of NH$_2$OH as a direct precursor of N$_2$O was investigated in Scen_HAO. Under aerobic conditions, NH$_2$OH oxidation produced more N$_2$O than NH$_4^+$ oxidation. In addition, upon reaching anoxia the N$_2$O production rate also increased in the presence of NH$_2$OH (Figure 2, B). Under anoxic conditions (Scen_An_AOB) neither NH$_4^+$ nor NO$_2^-$ produced N$_2$O individually (SI-S6). The spike of NH$_2$OH yielded the largest amount of N$_2$O specific to the amount of nitrogen spiked, and NO$_2^-$ was not detected at the end of the experiment (NO$_2^-$ < 0.05 mgN/L). Hence, NH$_2$OH oxidation by AOB produces N$_2$O and does not require O$_2$. The addition of an electron acceptor like NO$_3^-$ to ongoing anoxic NH$_2$OH oxidation increased the net N$_2$O production rate, while addition of an electron donor as NH$_4^+$ did not (SI-S6).

Taken together, the N$_2$O production observed in all the scenarios can only be effectively predicted using the NDHA model compared to other N$_2$O models, especially the DO-independent N$_2$O production from NH$_2$OH oxidation and no NO$_2^-$ production (Ding et al., 2016; Domingo-Félez and Smets, 2016; Ni et al., 2014; Pocquet et al., 2016).

### 3.2.1. Parameter estimation from N$_2$O dynamics

In the absence of stripping, heterotrophic denitrification is the only N$_2$O consuming process. First, the N$_2$O consumption potential of the biomass was estimated and the reduction factor was considered representative for the 4-step heterotrophic denitrification processes ($\eta_{HD} = 0.055$) (Figure 5, A). Then, N$_2$O production observed from NH$_4^+$ oxidation at high DO, where the interference of the two denitrifying pathways is minimum, was used to calibrate the NN pathway. $\varepsilon_{AOB}$, the most sensitive parameter at high DO was calibrated, $\varepsilon_{AOB} = 0.00048$ (Figure 5, B, SI-S2). Experiments from Scen_AMO were designed to reach anoxia at varying HNO$_2$
concentrations (0.15-3 μgN/L). Parameters associated to the ND pathway were the most sensitive and were thus calibrated ($\eta_{NOR} = 0.16$, $K_{AOB,HNO2} = 0.67$ μgN/L, $K_{NH2OH,ND} = 0.25$ mgN/L) (SI-S2, S7). The abiotic contribution measured was low and not considered during parameter estimation (SI-S6). A total of five parameters could be estimated from the N$_2$O datasets of all the scenarios (Table 2).

Validation of model response and secondary substrate (N$_2$O) parameter estimates

The calibrated NDHA model described the N$_2$O production dynamics and yield observed in the calibration datasets (F-test = 1). In all but one of the assays randomness was the most important part of the error based on the MSEP analysis (SI-S5). After calibration the ARIL narrowed by 58% from the original resolution and the PUCI increased by 71% ($n = 6$ assays).

The predictive ability of the model was evaluated on three batches with lower HNO$_2$ and with higher NH$_2$OH pulses (HNO$_2$ < 0.15 μgN/L, NH$_2$OH = 2 mgN/L). The average Janus coefficient of the validation prediction was 1.57 and $R^2$ was 0.985, indicating a good validation (Figure 5, D, E, F). Hence, the NDHA model could describe the N$_2$O production rates at a range of DO and HNO$_2$ concentrations.

The simple experimental design allowed the isolation of the various components of N$_2$O dynamics during NH$_4^+$ oxidation, and the parameter estimation procedure the identification of relevant model parameters.

3.3. Model predictions under varying DO and HNO$_2$: Scenario analysis

To investigate the effect of DO and HNO$_2$ on N$_2$O production the NDHA model was evaluated at varying DO and HNO$_2$ concentrations at pH = 7.5 (Figure 6) with the newly estimated parameters. The model predicted the largest N$_2$O emission at the lowest DO and high HNO$_2$ (> 20%, SI-S8); and the lowest N$_2$O emission at the highest DO and lowest HNO$_2$ (0.13%). The effect of increasing HNO$_2$ is seen at every DO level (DO$_{0.3}$: 0.33 → 5.4%, DO$_{5.0}$: 0.13 → 0.28%).
Conversely, increasing DO lowered the N$_2$O emission factor regardless of the HNO$_2$ level. The NO emission showed an increasing pattern with HNO$_2$ but a minimum was found at DO = 2.0 mg/L, further increasing at higher DO (SI-S8).

The contribution of the NN pathway was maximum when HNO$_2$ was not present and decreased with increasing HNO$_2$, at a faster rate at lower than at higher DO (2.4 and 47% respectively). The ND contribution followed opposite trends, indicating a shift between autotrophic pathways driven by HNO$_2$ and DO. The ND contribution increased with HNO$_2$, at a steeper rate at lower DO (97.4%) than at higher (53%). The HD contribution was maximum at low DO and high HNO$_2$ but only reached 0.2% (SI-S8).

[Figure 6]
4. Discussion

4.1. Parameter estimation from respirometric assays: oxygen consumption

The respirometric experiments were used to investigate the oxygen-consuming processes driven by the AOB-enriched biomass in the presence of reduced N-species (NH$_4^+$, NH$_2$OH and NO$_2^-$). If a model captures accurately the relevant oxygen-consuming processes, then DO and the primary N-substrates are predicted accurately. The experimental design based on the concatenated oxygen consumption allowed the isolation of individual processes independently (endogenous $\rightarrow$ NO$_2^-$ $\rightarrow$ NH$_4^+$) (Chandran and Smets, 2005).

The calibrated model could describe the endogenous oxygen uptake and NO$_2^-$ oxidation in Scen_NOB. However, because of the low NOB abundance the oxygen consumption from NO$_2^-$ oxidation was low, shown by a similar sensitivity of NOB and endogenous parameters to oxygen consumption after NO$_2^-$ spikes (Figure 3).

In Scen_AMO oxygen consumption was very sensitive to NH$_4^+$ dynamics (SI-S2), which yielded precise estimates for $\mu_{AOB,AMO}$, $K_{AOB,NH3}$ and $K_{AOB,O2,AMO}$ (Table 2). The maximum AOB growth rate ($\mu_{AOB,AMO} = 0.49$ 1/d) is in the low range of literature values found for N. europaea (0.56-1.62 1/d) (Brockmann et al., 2008). The biomass concentration ($X_{AOB}$), growth yield ($Y_{AOB}$) and maximum growth rate cannot be simultaneously identified from short experiments solely with DO data (Ellis et al., 1996; Petersen et al., 2001). Hence, the estimated growth rate is linearly dependent on the fixed values for $X_{AOB}$ and $Y_{AOB}$: a lower initial condition for $X_{AOB}$ would yield a higher estimate for $\mu_{AOB,AMO}$. Overall, the maximum specific NH$_4^+$ oxidation, 7.54±0.1E-05 gN/gVSS$_{AOB}$/h, was similar to other literature values for an AOB-enriched biomass (Ciudad et al., 2006). For the same NH$_4^+$ concentration, the higher oxygen consumption rate observed at higher pH was predicted by considering NH$_3$ the true substrate. The estimated affinities for both NH$_4^+$ oxidation substrates ($K_{AOB,NH3} = 0.12$ mgN/L, $K_{AOB,O2,AMO} = 0.23$ mg/L) were in range of literature values (Magri et al., 2007; Park and Noguera, 2007).

Overall, the precision of the identified parameter was high (CV < 7%), common from respirometric studies (Petersen et al., 2001). It should be noted that the concentration of the spikes
did not include uncertainty and was not estimated, which decreased the uncertainty of model predictions (Gernaey et al., 2002).

4.2. Role of NH$_4^+$ oxidation intermediates on N$_2$O production: experimental and modelling results

Nitrification plays an important role on N$_2$O emissions from N-removing systems, where NH$_4^+$, NO$_2^-$ and DO are the main substrates. Experimental results indicated that aerobic NH$_4^+$-oxidation products, NH$_2$OH and NO$_2^-$ were responsible for the higher N$_2$O production rate at the onset of anoxia and not NH$_4^+$ itself, which requires molecular O$_2$ for its oxidation (Sayavedra-Soto et al., 1996) (SI-S6). NH$_2$OH has been shown to be a key compound regulating N$_2$O production by AOB (Caranto et al., 2016; de Bruijn et al., 1995; Kozlowski et al., 2016). Because of its high reactivity under aerobic and anoxic conditions, it is an important electron donor for the cytochrome pool of AOB. Previous studies have shown the higher N$_2$O yield of nitrifying biomass and pure cultures fed on NH$_2$OH compared to NH$_4^+$, also observed in Scen_HAO (N$_2$O$_{R_{NH2OH}}$/N$_2$O$_{R_{NH4+}} = 40) (Figure 2) (Kim et al., 2010; Kozlowski et al., 2016). Here we show that even under anoxic conditions the sole presence of NH$_2$OH also yields a large amount of N$_2$O (SI-S6), suggested as a new N$_2$O producing pathway by (cyt) P460 (Caranto et al., 2016). The addition of an electron donor like NO$_2^-$ further increased N$_2$O production, highlighting the role of the primary N-substrates on N$_2$O dynamics, especially of NH$_2$OH.

The NDHA model captures the observed anoxic NH$_2$OH oxidation to N$_2$O with no HNO$_2$ production associated. A NH$_2$OH pulse in the concentration range of reported measurements (0.1mgN/L) could be described in the calibration dataset (Figure 5, F-test = 1, R$^2 > 0.99$); and at higher NH$_2$OH concentrations (2 mgN/L) the model predicted the N$_2$O trend but not as accurately (Figure 5, F-test = 0, R$^2 = 0.97$). Anoxic NH$_2$OH oxidation to NO has been recently proposed by Caranto and Lancaster (2017) as the HAO-catalyzed reaction, where NO$_2^-$ is produced only under aerobic conditions. The NO and NO$_2^-$ producing reactions, together with the anoxic NO reduction to N$_2$O are captured by the NDHA model (SI-S10, Process 2, 3, 5). Based on the model structure
of other two-pathway models for AOB none can predict the observed \( \text{N}_2\text{O} \) dynamics. In certain models \( \text{NH}_2\text{OH} \) does not react under anoxic conditions (Ding et al., 2016; Pocquet et al., 2016), or reacts producing both \( \text{N}_2\text{O} \) and \( \text{HNO}_2 \) (Ni et al., 2014).

Under a variety of DO, \( \text{HNO}_2 \) and \( \text{NH}_3 \) concentrations the calibrated NDHA model could describe the observed \( \text{N}_2\text{O} \) dynamics. Other models, with varying degrees of complexity, have also described the effect of \( \text{HNO}_2 \) and DO (4-6 processes) but the effect of \( \text{NH}_2\text{OH} \), the main driver of \( \text{N}_2\text{O} \) production, was not considered (Ding et al., 2016; Ni et al., 2014). The scenario analysis indicated a shift between the main pathway contributions governed by DO and \( \text{HNO}_2 \) (Figure 6). This relationship has been described by other two-pathway models, where ND was the main contributor to the \( \text{N}_2\text{O} \) emission factor during \( \text{NH}_4^+ \) oxidation and the highest \( \text{N}_2\text{O} \) emission factor was observed at low DO (Ni et al., 2014; Pocquet et al., 2016).

4.3. \( \text{N}_2\text{O} \) model calibration

4.3.1. Analysis of the NDHA parameter estimates.

In the last years new \( \text{N}_2\text{O} \) models have improved their best-fit predictions under different scenarios (i.e. varying DO, \( \text{NO}_2^- \)) by increasing the number of processes and variables considered. For example, all the models describe the ND pathway with a \( \text{NO}_2^- \) dependency (Ni et al., 2011; Pocquet et al., 2016; Schreiber et al., 2009), or the NN pathway as a fraction of the \( \text{NH}_2\text{OH} \) oxidation to \( \text{NO}_2^- \) (Ni et al., 2014; Pocquet et al., 2016). While the intermediates of \( \text{NH}_4^+ \) oxidation or the process rates are described differently, some parameters are common across \( \text{N}_2\text{O} \) models.

In this study, the contribution of the NN pathway (\( \varepsilon_{\text{AOB}} = 0.048\% \mu\text{AOB.HAO} \)) is in the low range of other reported values (0.052-0.15%), while the maximum \( \text{N}_2\text{O} \) production rate, described by \( \eta_{\text{NOR}} = 0.16 \), lies in the range (0.07 – 0.34). In agreement with the ND description of the model by Pocquet et al., (2016), the electron acceptor of the ND pathway was \( \text{HNO}_2 \) instead of \( \text{NO}_2^- \).

Increasing \( \text{N}_2\text{O} \) production rates were observed at higher \( \text{HNO}_2 \) but constant \( \text{NO}_2^- \) (9.5-10mgN/L, 0.8-1.5 \( \mu \text{gHNO}_2\text{-N/L} \)). The affinity for \( \text{HNO}_2 \) (\( K_{\text{AORB,HN02}} = 0.67 \mu \text{gHNO}_2\text{-N/L}, 17.1 \text{ mg NO}_2^-\text{-N/L}, \text{pH 7.5, 20 }^\circ\text{C} \)) could be estimated from experiments run at varying \( \text{HNO}_2 \) (0.16-1.5 \( \mu \text{gHNO}_2\text{-N/L} \)).
The affinity for NO$_2^-$ is 100 times lower than other nitrifying systems, but 15 times higher than a NO$_2^-$-accumulating biomass ($K_{\text{AOB.NO2-}} = 0.14$, 282 mgN/L)(Pocquet et al., 2016; Schreiber et al., 2009). The difference could be explained by the operating conditions at which each biomass is acclimated: low NO$_2^-$ for activated sludge systems ($\approx 0.5$mgN/L) and high NO$_2^-$ for nitritating reactors (50-150 mg NO$_2^-$-N/L in the parent reactor of this study). The NDHA model combined with the experimental design allows the simultaneous estimation of parameters describing main N-substrates and N$_2$O dynamics from simple respirometric experiments.

### 4.3.2. N$_2$O models: response validation and identifiability

As N$_2$O models produce better fits discrimination tools become more important. If the capabilities of two models to describe dynamic N$_2$O trends are similar (Lang et al., 2017; Pan et al., 2015) visual inspection or metrics such as $R^2$ are not sufficient, and more rigorous statistics as the F-test used in this study are necessary for model discrimination.

The parameter subset selection during calibration of each scenario was based on the lower AIC criteria. The identifiability of the estimated parameters was assessed by the correlation matrix and the precision of the estimated parameters ($CV < 5\%$). The triplet $K_{\text{AOB.HNO2}}, K_{\text{AOB.NH2OH.ND}}$ and $\eta_{\text{NOR}}$ were estimated with the same dataset, and based on their collinearity index ($\gamma > 15$) they are not identifiable and their values depend on the others. This metric is based on local sensitivities, and as shown in (Table 2), the high correlation between $K_{\text{AOB.NH2OH.ND}}$ and $\eta_{\text{NOR}}$ could be responsible for the high collinearity of the triplet. An improved experimental design or an additional dataset such as NO would improve the identifiability these parameters, as shown for other two-pathway N$_2$O models (Pocquet et al., 2016). Together with the best-fit prediction the 95% CI of the calibrated NDHA model bracketed the experimental datasets, validating the model response.

The uncertainty of estimates ($CV$, correlation matrix) is not always reported in literature (Ding et al., 2016; Kim et al., 2017; Spérandio et al., 2016), which hampers critical discrimination procedures. While some models have reported the estimated variance identifiability metrics are
scarce and not assessed. To the authors knowledge none of the proposed N$_2$O models has studied how the uncertainty of parameter estimates affects N$_2$O predictions (e.g. ARIL, PUCI). Moreover, the analysis of residuals shows that high frequency data such as online sensors are not totally discrete and can lead to autocorrelated residuals in N$_2$O measurements (SI-S5). When residuals are not independent not every point contains information for model validation, which leads to underestimation of the parameter uncertainty (CV $<< 0.001\%$ (Peng et al., 2015)).

Hence, while very high precision of estimates is possible, testing the model response can avoid a possible over interpretation of the dataset. In this study we show that addressing parameter identifiability after model calibration will benefit N$_2$O model discrimination studies.

### 4.4. N$_2$O model uncertainty

With the final objective of designing N$_2$O mitigation strategies, the confidence of model predictions is critical when quantifying N$_2$O emissions. As a by-product of NH$_4^+$ oxidation, the uncertainty associated to NH$_4^+$ removal processes will propagate to N$_2$O predictions. The respirometric experimental design allowed for accurate estimates and narrow 95% confidence intervals for DO, NH$_4^+$ and other N-species, which was critical to reduce the predicted uncertainty for N$_2$O (SI-S9). N$_2$O models have been calibrated by sequentially fitting the primary N-substrates followed by the N$_2$O dynamics (Ni et al., 2014; Pocquet et al., 2016). The effect of propagating the uncertainty from the calibration of primary N-substrates to N$_2$O was not discussed. Consequently, the precision of the N$_2$O calibration could be overestimated.

To evaluate the performance of the parameter estimation results N$_2$O emissions from a simulated case study were examined via Monte-Carlo simulations (pH = 7.5, NH$_4^+$ = 70 mgN/L, DO = 0.3, 1.3 mg/L and NO$_2^-$ = 0, 1, 5, 15, 100 mgN/L, 500 simulations). At pseudo-steady state the standard error of the Monte-Carlo simulations shows the propagated uncertainty. For the 10 parameters estimated in this study the normalized uncertainty associated to their default class (Sin et al.,
2009) is approximately 40% of the N$_2$O emission factor (Figure 7). If the calibration results from this experimental design are considered instead (Table 2), the uncertainty decreases to 10% (Figure 7). These results highlight the importance of considering uncertainty propagation in N$_2$O predictions, as N$_2$O emissions are greatly affected by the uncertainty of primary N-substrates.

Conclusions

- A novel experimental design to calibrate N$_2$O models through extant respirometry is proposed that combines DO and N$_2$O measurements.
- Parameters associated to NO$_3^-$ and NH$_4^+$ oxidation were sequentially fitted to DO consumption profiles by isolating individual processes. Five parameters were identified from the DO dataset and another five were estimated from the N$_2$O dataset with low uncertainty (CV < 10%).
- The NDHA model response was validated and described AOB-driven N$_2$O production at varying DO and HNO$_2$ concentrations.
- For the first time the uncertainty of the calibrated parameters was propagated to the model outputs in a simulation case study, and compared to the uncertainty from a reference case. The uncertainty of the N$_2$O emission factor predicted was reduced from $\sim$ 40% of its value to $\sim$ 10%.

Software availability

The MATLAB/SIMULINK code containing the implementation of the model is free upon request to the corresponding author.

Acknowledgements

This research was funded by the Danish Agency for Science, Technology and Innovation through the Research Project LaGas (12-132633). The authors have no conflict of interest to declare.
References


hold the key? Trends Biotechnol. 27, 388–97. doi:10.1016/j.tibtech.2009.03.009


Figure 1 – Schematic of the parameter estimation procedure.
Figure 2 – Dissolved oxygen and liquid nitrous oxide concentrations during experiments: Scen_NOB (NO\textsubscript{2}− pulses) (A), Scen_HAO (NH\textsubscript{2}OH pulses) (B) and Scen_AMO (NH\textsubscript{4}+ pulses) (C) (3-4.5 mgN/L).
Figure 3 – Parameter sensitivity ranking of scenarios used during calibration for DO (white background) and N₂O (grey background). Scen_NOB (left), Scen_AMO (middle and right). (*) Parameters not considered for calibration. The error bars correspond to the standard deviation between experiments of the same scenario.
Figure 4 – Experimental DO, NH$_4^+$ and NO$_2^-$ (blue markers) and model predictions (black line best-fit, red lines 95% CI). Datasets from Scen_AMO, calibration: A and B; validation: C and D.
Figure 5 – Experimental N$_2$O (black) and DO (blue), and model predictions (dark line best-fit, light lines 95% CI) for the N$_2$O calibration. Datasets from calibration: (A) Scen_An_HB (N$_2$O pulse), (B) Scen_AMO (Aerobic NH$_4^+$ pulse), (C) Scen_An_AOB (Anoxic NH$_3$OH pulse). Datasets from validation: (D, E) Scen_AMO (Aerobic → anoxic NH$_3^+$ pulse), (F) Scen_An_AOB (NH$_3$OH pulse).
Figure 6 – Scenario analysis using the validated NHDA simulation model. Simulations were run under constant DO levels (0.1 - 0.3 - 0.5 - 1.0 - 2.0 - 3.5 - 5.0 mg/L), NO$_2^-$ (0 – 1 – 4 – 10 – 20 – 90 – 340 mgN/L). (Left) N$_2$O emission factor (% N$_2$O/NH$_4^+$), colorbar: 0 – 5%, blue - red. (Middle, Right) NN, ND Pathway contribution (-), colorbar: 0 – 1, black - white.
Figure 7 – Model evaluation results (500 runs) at pseudo-steady state for NH$_4^+$ removal at constant DO and NO$_2^-$: AOB-enriched biomass, pH = 7.5, NH$_4^+$ = 70 mgN/L, DO ([0.3 – 1.3] mg/L) and NO$_2^-$ [0 – 15 – 100] mgN/L. (Top) N$_2$O emission factor at low DO (red) and high DO (light red); top standard error corresponds to uncertainty of estimated parameters only (Table 2), bottom standard error corresponds to uncertainty in All model parameters. (Bottom) Normalized variance for uncertainty considered in All model parameters (dark grey) or only for the 10 parameters estimated in this study (light grey) (Table 2) with default uncertainty (top bar) or from this study (Table 2) (bottom bar).