

# A Calibration Approach towards Reducing ASM2d Parameter Subsets in Phosphorus Removal Processes

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**Abstract**—A novel calibration approach that aims to reduce ASM2d parameter subsets and decrease the model complexity is presented. This approach does not require high computational demand and reduces the number of modeling parameters required to achieve the ASMs calibration by employing a sensitivity and iteration methodology. Parameter sensitivity is a crucial factor and the iteration methodology enables refinement of the simulation parameter values. When completing the iteration process, parameters values are determined in descending order of their sensitivities. The number of iterations required is equal to the number of model parameters of the parameter significance ranking. This approach was used for the ASM2d model to the evaluated EBPR phosphorus removal and it was successful. Results of the simulation provide calibration parameters. These included  $Y_{PAO}$ ,  $Y_{PO_4}$ ,  $Y_{PHA}$ ,  $q_{PP}$ ,  $\mu_{PAO}$ ,  $b_{PAO}$ ,  $b_{PP}$ ,  $b_{PHA}$ ,  $K_{PS}$ ,  $Y_A$ ,  $\mu_{AUT}$ ,  $b_{AUT}$ ,  $K_{O_2 AUT}$ , and  $K_{NH_4 AUT}$ . Those parameters were corresponding to the experimental data available.

**Keywords**—ASM2d, calibration approach, iteration methodology, sensitivity, phosphorus removal

## I. INTRODUCTION

ACTIVATED sludge models (ASMs) have been used to understand microorganism mechanisms in activated sludge processes in order for design, upgrade or optimize of various wastewater treatment plants (WWTPs) [1], [2]. To study carbon, nitrogen and phosphorus removal, Activated Sludge Model No. 2d (ASM2d) is an essential model because it simulates the dynamics of biological mechanisms in enhanced biological phosphorus removal (EBPR) systems [3]. ASM2d can explain phosphorus utilization by phosphorus-accumulating organisms (PAOs) under aerobic conditions as well as denitrification mechanisms of PAOs. In contrast, Activated Sludge Model No. 2 (ASM2) can describe phosphorus uptake mechanisms under aerobic conditions only. However, the ASM2d model is complicated to calibrate. This is due to a requirement of large number of the model parameters. These are most often derived from the information content of particular wastewater treatment plants (WWTPs) [4]–[6]. The Modified University of Cape Town (MUCT) processes have been widely used in activated sludge WWTPs for prevention of eutrophication [13]–[15]. Also, the MUCT processes are among the most effective for EBPR. This is due their design maintaining truly anaerobic conditions for EBPR [16], [17].

Other researchers [2] reported that the model is over-parameterized due to the paucity of experimental observations. Therefore, the reduction of the number of parameters that are required for calibration would make the model more user friendly but it is challenging. Currently, there are two calibration approaches to reduce the number of required parameters. They are (1) the identifiability approach, and, (2) the experience-based approach. Mathematical analysis is used for the identifiability determination. That is to say, there is an ordered determination of the magnitude of influenced for each model parameter. It is based on sensitivity analysis as the priority step. The result is a calculation of parameter ranking following determination of the parameter subset sizes. This requires high levels of computer resources and performance [4]–[7]. In contrast, the experience-based approach requires process knowledge of particular activated sludge unit operations to derive model parameters [8]–[12]. In using the experience based approach for this study, values for process parameters were obtained from literature published by other researchers. Both approaches are feasible methods to successfully attain modeling calibration. Each achieves values for the necessary stoichiometric and kinetic parameters and satisfies the simulation. The identifiability approach has the disadvantage of high computational demands for large data subset sizes [2]. The experience-based approach poses difficulty in choosing modeling parameters according to knowledge and experience with particular activated sludge WWTPs under study. This study is unique in that it employs both methods, rather than just one.

Regarding the limitations of the two calibration approaches discussed above, a new approach is purposed in this study. There are two important considerations needed to completely develop model calibration. These are (1) sensitivity analysis and (2) iteration in the calibration methodology. The sensitivity calculation produces a parameter significance ranking which is used to reduce the number of iterations required. It further represents the influence of model parameters on the simulation output [4]–[7]. Then using the parameter significance ranking, the calibrated parameters are determined iteratively.

The purpose of this research is to present a new calibration approach. The goal was to avoid both high calculation demands and the requirement for a priori knowledge of all the parameters specific to the activated sludge treatment works.

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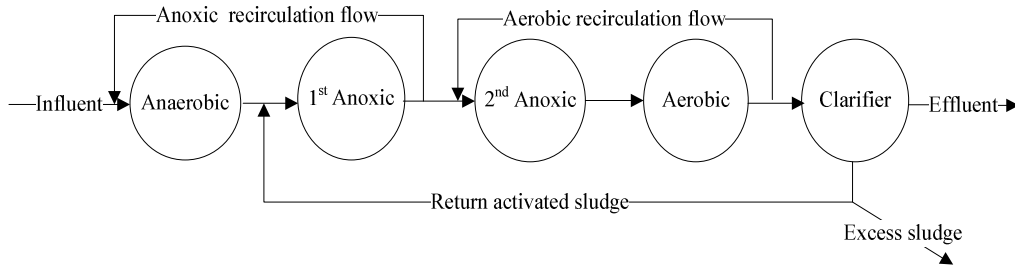


Fig. 1 A schematic diagram of the activated sludge MUCT

This new method was developed using the identifiability approach and the experience-based approach. The sensitivity method is used to reduce the number of model parameters. Parameter sensitivity is used to identify those parameters which most affect the model. Additionally, the model is calibrated using an iterative process. This avoids high computational demand. This was to reduce the size of ASM2d parameter subset. Four procedures were structured in this new approach. Firstly the analysis of the wastewater characterization and layout of the related to a specific wastewater treatment plant were established. Second, defining initial default values of ASM2d parameters and demonstration of the range values for stoichiometric and kinetic parameters were obtained from the literature. Third, analyzing the sensitivity of the ASM2d parameters was done using the experimental results of an activated sludge on a pilot-scale process to obtain the parameter significance ranking. Finally, model parameter values were refined by iteratively fitting them to the observed experimental results. This was done sequentially starting with the most significant parameter, continuing with subsequent parameters in order of decreasing impact upon the model.

## II. MATERIALS AND METHODS

### A. The MUCT Pilot Scale of EBPR Processes

The results of the modeling calibration were determined experimentally using the MUCT pilot scale processes operated in the pilot hall facilities of the sewage treatment works of Cranfield University, UK. This pilot scale processes (Fig. 1) consisted of five reactors in series. They included anaerobic, 1<sup>st</sup> anoxic, 2<sup>nd</sup> anoxic, aerobic phase and clarifier stages with effective volumes 125 L, 120 L, 230 L, 550 L and 334 L, respectively. The solid retention time (SRT) was 15 days. The operating conditions of this system were: influent wastewater flow rate ( $Q_{IN}=60$  L/h), return activated sludge flow rate ( $Q_R=51$  L/h), anoxic recirculation flow ( $Q_1=60$  L/h) and aerobic recirculation flow ( $Q_2=60$  L/h). In order to develop EBPR processes, acetic acid was fed to influent. The experimental samples were observed on a daily basis for the influent, anaerobic and aerobic stages as well as for the effluent. Average process temperature was maintained at 17°C. The process was fed with municipal wastewater.

### B. Sensitivity Analysis

The relative importance of parameters over the range of model inputs was calculated to evaluate the kinetic and stoichiometric parameters. This determined the parameters that most affect the effluent. Sensitivity analysis results in an ordered ranking of parameters based upon the magnitude of their influence on the model [15]. The data used for the sensitivity analysis included values for total chemical oxygen demand (TCOD), total nitrogen (TN), total phosphorus (TP), phosphorus (P), total suspended solid (TS), mixed liquor suspended solid (MLSS), ammonium ( $NH_4$ ), and nitrate ( $NO_3$ ). The sensitivity calculations were implemented in relation to the following dimensional functions:

$$s_{i,j} = \frac{\Delta\theta_j}{sc_i} \frac{\partial y_i}{\partial \theta_j}, \quad \tilde{s}_{i,j} = \frac{s_{i,j}}{\sqrt{\sum_{k=1}^n s_{k,j}^2}} \quad (1)$$

The matrices  $S = (s_{i,j})$  and  $\tilde{S} = (\tilde{s}_{i,j})$ , and the column vectors

$$s_j = (s_{1,j}, \dots, s_{n,j})^T \text{ and } \tilde{s}_j = (\tilde{s}_{1,j}, \dots, \tilde{s}_{n,j})^T$$

where  $\partial y_i / \partial \theta_j$  is the absolute sensitivity of the model output  $y$  to the parameter  $\theta_j$  at a particular time. The matrices,  $S$  and  $\tilde{S}$ , contain values of the various sensitive parameters. A finite difference method is used to approximate the absolute sensitivity value, which the significant limitation of this method is only valid for a small change in the parameter considered [2]. The vectors  $\tilde{s}_j$  are defined as normalization:  $\tilde{s}_j = s_j / \|s_j\|$ . The  $\Delta\theta_j$  value is the uncertainty range of the parameter  $\theta_j$  according to prior knowledge which is classified into three uncertainty classes and  $sc_i$  is a characteristic scale of the variable  $y_i$  [18]. Aquasim [19] and interface UNSIM [20], [21] were used to calculate the sensitivity analysis.

### C. Iteration Methodology in the New Calibration Approach

Using all possible stoichiometric and kinetic parameters values in model would prevent calibration accuracy [22]. Such calculations would require a very long time, i.e. perhaps several days. Additionally, round off and truncation errors may be introduced and grow during the calculations. Our approach, therefore, employed the use of parameter subsets.

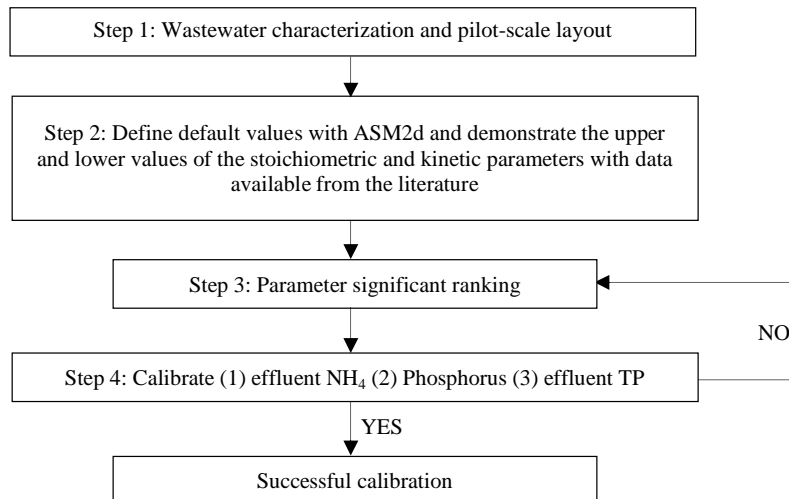


Fig. 2 A new calibration approach procedures to reducing ASM2d parameter subsets

Some parameters had to be categorized by the iteration tool into specific groups. These included nitrification, phosphorus removal and others, based on the available experimental data. Sensitivity parameter functions were used in the implementation iteration with GPS-X (Hydromantis, Inc., Hamilton, Canada). The procedures for that iteration calibration are shown in Fig. 2. A stepwise manual iteration methodology was specifically adapted to EBPR in which the simulation results were calibrated using observed results with the parameter significance ranking in order to achieve a reasonable model fit. The iterative algorithm was reevaluated until refinement of the sensitivity parameters no longer affected the simulation output.

### III. RESULTS AND DISCUSSION

#### *Step1: Influent Wastewater Characteristics*

The simulation of operating period was completed for a steady state processes. The influent characteristics are summarized in TABLE I.

#### *Step2: Default Values and a Priori Parameter Set*

In order to calibrate the ASM2d model, a number of default parameters were established. Their values were obtained from published literature. These included kinetic and stoichiometric parameters of phosphorus accumulating organisms (PAOs). Maximum and minimum values for these parameters are given in TABLE II.

TABLE I  
CHARACTERIZATION OF INFLUENT WASTEWATER COMPONENTS

Symbol	Definition	Influent	Unit	Reference
$S_{O_2in}$	Dissolved oxygen	0	$g\ O_2/m^3$	This study
$S_{Ain}$	Fermentation products (acetate)	103.25	$g\ COD/m^3$	This study
$S_{Fin}$	Readily biodegradable substrate	26.93	$g\ COD/m^3$	This study
$S_{Fin}$	Inert soluble organic substrates	53.50	$g\ COD/m^3$	This study
$S_{NH_4in}$	Ammonium	33.53	$g\ N/m^3$	This study
$S_{NO_3in}$	Nitrate (plus nitrite)	0	$g\ N/m^3$	This study
$S_{PO_4in}$	Phosphate	5.04	$g\ P/m^3$	This study
$S_{N_2in}$	Dinitrogen ( $N_2$ ), 0.78 atm at 20 °C	0	$g\ N/m^3$	This study
$X_{Fin}$	Inert, non-biodegradable organics	168.00	$g\ COD/m^3$	This study
$X_{Sin}$	Slowly biodegradable substrate	43.68	$g\ COD/m^3$	This study
$X_{PAOin}$	Phosphorus-accumulating organisms, PAO	0	$g\ COD/m^3$	[3]
$X_{PPin}$	Stored poly-phosphate of PAO	0	$g\ P/m^3$	[3]
$X_{PHAin}$	Organic storage products of PAO	0	$g\ COD/m^3$	[3]

TABLE II  
DEFAULT, MINIMUM AND MAXIMUM VALUES FOR PARAMETERS INVOLVED ON ASM2D CALIBRATION.

Symbol	Definition	Default	Min.	Max.	Unit	Reference
Typical stoichiometric parameter						
$Y_H$	Yield coefficient	0.625			g COD/g COD	[3]
$F_{XI}$	Fraction of inert COD generated in biomass lysis	0.10			g COD/g COD	[3]
$Y_{PO_4}$	Poly-phosphate (PP) requirement ( $PO_4$ release) per poly-hydroxy-alkanoates (PHA) stored	0.40	0.26	0.46	g P/g COD	[3], [25], [26], [28], [29], [31], [36]
$Y_{PAO}$	Yield coefficient (Biomass/PHA)	0.625	0.58	0.9	g COD/g COD	[3], [25], [28], [36]
$Y_{PHA}$	PHA requirement for PP storage	0.20	0.20	0.32	g COD/g P	[26], [36]
$Y_A$	Yield coefficient (Biomass/Nitrate)	0.24			g COD/g N	[3]
Phosphorus-Accumulating Organisms, PAOs						
$q_{PHA}$	Rate constant for storage of $X_{PHA}$ (base $X_{PP}$ )	3.00	0.36	9.03	g $X_{PHA}$ /g $X_{PAO}$ /d	[3], [23], [24], [25], [26], [28], [29], [31], [36]
$q_{PP}$	Rate constant for storage of $X_{PP}$	1.50	1	10.88	g $X_{PP}$ /g $X_{PAO}$ /d	[3], [24], [25], [26], [28], [29], [31], [36]
$\mu_{PAO}$	Maximum growth rate of PAO	1.00	0.67	2.97	d <sup>-1</sup>	[3], [25], [26], [28], [29], [36]
$\eta_{NO_3}$	Reduction factor for anoxic activity	0.60	0.44	0.60		[3], [28]
$b_{PAO}$	Rate for Lysis of $X_{PAO}$	0.20	0.04	0.27	d <sup>-1</sup>	[3], [24], [25], [26], [27], [28], [29], [36]
$b_{PP}$	Rate for Lysis of $X_{PP}$	0.20	0.03	0.20	d <sup>-1</sup>	[3], [24], [26], [27]
$b_{PHA}$	Rate for Lysis of $X_{PHA}$	0.20	0.08	0.20	d <sup>-1</sup>	[3], [26], [28], [36]
$K_{O_2}$	Saturation/inhibition coefficient for oxygen	0.20	0.20	0.20	g O <sub>2</sub> /m <sup>3</sup>	[3], [36]
$K_{NO_3}$	Saturation coefficient for nitrate, $S_{NO_3}$	0.50	0.50	0.50	g N/m <sup>3</sup>	[3], [36]
$K_A$	Saturation coefficient for acetate, $S_A$	4.00	1.00	32.00	g COD/m <sup>3</sup>	[3], [25], [28], [29], [36], [23]
$K_{NH_4}$	Saturation coefficient for ammonium (nutrient)	0.05	0.01	0.05	g N/m <sup>3</sup>	[3], [31], [36]
$K_{PS}$	Saturation coefficient for phosphorus in storage of PP	0.20	0.20	0.50	g P/m <sup>3</sup>	[3], [26], [36]
$K_P$	Saturation coefficient for phosphate (nutrient)	0.01	0.01	3.00	g P/m <sup>3</sup>	[3], [23], [27], [36]
$K_{ALK}$	Saturation coefficient for alkalinity (HCO <sub>3</sub> )	0.10	0.02	0.10	mole HCO <sub>3</sub> /m <sup>3</sup>	[3], [30], [36]
$K_{MAX}$	Maximum ratio of $X_{PP}/X_{PAO}$	0.34	0.152	0.37	g $X_{PP}$ /g $X_{PAO}$	[3], [25], [28], [29], [36]
$K_{PP}$	Saturation coefficient for poly-phosphate	0.01	0.01	0.26	g $X_{PP}$ /g $X_{PAO}$	[3], [23], [36]
$K_{IPP}$	Inhibition coefficient for PP storage	0.02	0.001	0.48	g $X_{PP}$ /g $X_{PAO}$	[3], [23], [25], [28], [29], [36]
$K_{PHA}$	Saturation coefficient for PHA	0.01	0.001	0.01	g $X_{PHA}$ /g $X_{PAO}$	[3], [24], [25], [28], [29], [36]
Autotrophs						
$K_{O_2AUT}$	Saturation coefficient for oxygen	0.5	0.1	1.0	g O <sub>2</sub> /m <sup>3</sup>	[26]
$K_{NH_4AUT}$	Saturation coefficient for ammonium (substrate)	1.00	0.3		g N/m <sup>3</sup>	[26]

### Step 3: Parameter Significance

The parameter significance ranking of the resulting sensitivity analysis was based on the total number of model outputs. The result showed which were the most significant of the data inputs, ie, when the roots of mean squared values of sensitivities were higher than 0. From this, the parameter subsets under these studies were reduced to the top 30 as shown in TABLE III. Consequently, the resulting 30 parameters were used to calibration in analyzing

allexperimental results. Other researchers [7] have used sensitivity parameter rankings with roots of mean squared values larger than 0.2 and found 11 relevant parameters that were used to calibrate the Activated Sludge Model No. 1 (ASM1) applied to full-scale plant data. Differences in parameter significance rankings among studies of ASM2d are highly influenced by the data available for calibration. Important factors in this regard include consideration of

TABLE III  
THE ASM2d PARAMETER SIGNIFICANT RANKING

Ranking	Parameter	Roots of mean squared of sensitivities
1	$Y_{PO4}$	26.43
2	$\mu_{PAO}$	23.45
3	$Y_{PAO}$	19.51
4	$q_{PP}$	18.35
5	$K_{O2\ AUT}$	18.01
6	$K_{NH4\ AUT}$	11.85
7	$b_{PP}$	8.93
8	$\mu_{AUT}$	7.99
9	$Y_{PHA}$	4.76
10	$b_{AUT}$	2.76
11	$b_{PHA}$	2.16
12	$Y_A$	1.59
13	$K_{IPP}$	1.29
14	$\mu_H$	1.11
15	$\eta_{NO3}$	1.01
16	$q_{PHA}$	0.94
17	$K_{PS}$	0.53
18	$K_{PP}$	0.47
19	$K_{AUT}$	0.23
20	$K_{ALK\ PAO}$	0.22
21	$f_{XI}$	0.07
22	$K_{PHA}$	0.04
23	$K_{NO3}$	0.03
24	$K_F$	0.02
25	$K_h$	0.02
26	$K_X$	0.01
27	$K_P$	0.01
28	$q_{Fe}$	0.01
29	$b_{PAO}$	0.01
30	$Y_H$	0.01

particular WWTP configurations and operation, and some properties of collected data [2]. The parameter significance ranking showed that temperature correction coefficients and the parameters for PAOs were among the most influential parameters on the model outputs. In this study, ASM2d was calibrated using an identifiability method to describe nitrogen and phosphorus removal in the Haaren (The Netherlands) WWTP [2]. PAOs play an important role in the dynamics of the EBPR processes [5]. In another application, this approach to ASM2d calibration used an identifiability analysis in a systematic manner. It was applied to EBPR at a full scale WWTP in Switzerland [5]. Additionally, to calibrate ASM2d for anaerobic/anoxic/oxic conditions (A2/O), a pilot WWTP used an identifiability approach [6]. PAOs parameters were also among the most sensitivity. Although other studies were in rough agreement, there were some differences. The parameter significance rankings of the current study are

different from that of other researchers [2], [5], [6]. In the current study, the parameter with the highest sensitivity was  $Y_{PO4}$ . However, other researchers found this parameter's sensitivity to be ranked as 8<sup>th</sup> [6], 15<sup>th</sup> [2], and it was excluded altogether in another study [5]. Also researchers [5] found that parameter  $b_{PAO}$  had the highest sensitivity although it ranked 4<sup>th</sup> and 27<sup>th</sup> in other studies [6], [2]. This parameter's sensitivity was ranked lower in the current study (29<sup>th</sup>). Considering the second most significant sensitivity ranking in this study,  $\mu_{PAO}$ , it was of the same order as in one study [5], but it was at a lower position (17<sup>th</sup>) in other work [2], [6]. Additionally, the current study found that  $\mu_{AUT}$  had a higher sensitivity ranking than other studies [2][5]. However its ranking was lower than reported elsewhere [6]. Furthermore the sensitivity analysis in other work [15] used only two parameters,  $Y_{PAO}$  and  $Y_{PO4}$ . Here anaerobic/aerobic/anoxic processes for simultaneous nitrogen and phosphorus removal on  $NO_3$  and  $PO_4$  profiles were examined. One group of researchers [33] used manually repeating simulation as a sensitivity approach to individual changes in the magnitude of related parameters for each model parameter. This was based on the steady state cyclic simulations of  $S_{PO4}$ ,  $X_{PHA}$ ,  $S_A$  and MLSS profiles containing the most sensitive parameters namely,  $Y_{PO4}$ ,  $q_{PHA}$ ,  $q_{PP}$ ,  $K_{PHA}$  and lysis rates.

#### Step 4: The Iteration Processes with Simulation of the ASM2d Modeling

The calibration approach here described avoids the problem of needing extensive experience in activated sludge modeling and the difficulty of identifiability analysis. This approach iterates only based upon the parameter sensitivity. A stepwise methodology was used in the mathematical simulations in each of the iterations. The iteration number of each experimental data set was based on the number of parameters in the sensitivity analysis. Use of 30 iterative steps for each of the parameter data sets, i.e. the same number of parameters in the sensitivity ranking, was used to predict the output of  $NH_4$  and TP in effluent and of  $PO_4$  in anaerobic phase. The application of parameter significance ranking was used to perform the calibration in order to fit the model's parameter values to the observed results. The most significant parameter was iterated. This was followed by each of the other 29 parameters included in the parameter significance ranking in order of decreasing influence. Iterations begun with the initial default parameter value and were carried out under the steady state conditions. The effluent  $NH_4$  is the first experimental data set used to calibrate the ASM2d parameter in order to observe the autotrophs activity. After calibration the values for each parameter were found. The results of the  $NH_4$  experiments are shown in TABLE IV. As a result of fitting the simulated data to the effluent  $NH_4$  concentration, it was found that there are five significant parameters. They are: yield of autotrophic biomass per unit of  $NO_3-N$  ( $Y_A$ ), the maximum growth rate for autotrophs ( $\mu_{AUT}$ ), the decay rate of  $X_{AUT}$  ( $b_{AUT}$ ), saturation coefficient for oxygen ( $K_{O2\ AUT}$ ), nitrogen half saturation coefficient for autotrophs ( $K_{NH4\ AUT}$ ).  $\mu_{AUT}$  was increased to sustain autotrophic growth.

TABLE IV  
THE VALUES OF THE CALIBRATED ASM2d PARAMETERS

Symbol	ASM2d	Calibrated value	Unit
Phosphorus-Accumulating Organisms, PAOs			
$Y_{PAO}$	0.625	0.60	g COD/g COD
$Y_{PO4}$	0.4	0.4	g P/g COD
$Y_{PHA}$	0.20	0.23	g COD/g P
$q_{PHA}$	3.0	3.5	g $X_{PHA}$ /g $X_{PAO}$ /d
$q_{PP}$	1.5	1.5	g $X_{PP}$ /g $X_{PAO}$ /d
$\mu_{PAO}$	1.0	1.0	d <sup>-1</sup>
$b_{PAO}$	0.2	0.2	d <sup>-1</sup>
$b_{PP}$	0.2	0.2	d <sup>-1</sup>
$b_{PHA}$	0.2	0.2	d <sup>-1</sup>
$K_{PS}$	0.2	0.35	g P/m <sup>3</sup>
Autotrophs			
$Y_A$	0.24	0.24	g COD/g N
$\mu_{AUT}$	1.0	1.2	d <sup>-1</sup>
$b_{AUT}$	0.15	0.05	d <sup>-1</sup>
$K_{O2AUT}$	0.5	0.5	g O <sub>2</sub> /m <sup>3</sup>
$K_{NH4AUT}$	1.00	0.15	g N/m <sup>3</sup>

Next  $b_{AUT}$  was decreased in relation to increasing autotrophic growth rate. Later  $K_{NH4AUT}$  decreased because of low ammonium concentration in the aerobic phase. Both  $Y_A$  and  $K_{O2AUT}$  were from the same as the default values. Comparison of the parameter subsets to other experiments using different protocols is shown in TABLE V. Significant parameters based upon  $NH_4$  in effluent using the experienced-based approach for the experiments of sequencing batch reactors (SBRs) [31] were calibrated. To accomplish this, nutrients were removed under limited aeration conditions. The parameters examined included  $\mu_{AUT}$  and  $K_{NH4}$ .

TABLE V  
THE PARAMETER SUBSETS IN DIFFERENT STUDIES

Parameter subsets	Reference
$Y_{PAO}, Y_{PO4}, Y_{PHA}, q_{PHA}, q_{PP}, \mu_{PAO}, b_{PAO}, b_{PP}, b_{PHA}, K_{PS}, Y_A, \mu_{AUT}, b_{AUT}, K_{O2AUT}, K_{NH4AUT}$	This study
$b_{PAO}, \mu_{PAO}, q_{PHA}, q_{PP}, b_{PP}, K_b, n_{Fe}, b_{AUT}, K_{NH4}, \mu_{AUT}$	[5]
$b_{PAO}, Y_{PO4}, \mu_{AUT}$	[6]
$\mu_{AUT}, \alpha_{XI}, \alpha_{SA}, \alpha_{SF}, n_{NO3HYD}, K_{PHA}, \mu_{PAO}$	[8]
$Y_H, \mu_H, K_F, b_H, n_{NO3}, \mu_A, K_{NH4}, b_A, Y_{PO4}, q_{PHA}, K_A, Y_{PAO}, \mu_{PAO}, q_{PP}, b_{PAO}, K_{PHA}, K_{IPP}, K_{MAX}$	[12]
$Y_{PAO}, Y_{PO4}$	[15]
$\mu_{AUT}, K_{NH4}, K_X, K_N, K_O, K_{OA}, Y_{HNO3}, b_H, Y_{PO4}, q_{PHA}, \mu_{PAO}, q_{PP}$	[31]
$\mu_{AUT}, b_{PAO}, b_{PP}, b_{PHA}, q_{PHA}, q_{PP}, K_{PHA}, Y_{PO4}$	[33]
$\mu_{AUT}, \alpha_{XI}, n_{NO3HYD}, K_b, n_{Fe}, \mu_H, K_{O2}, n_{NO3}, K_{NH4AUT}, q_{PHA}, q_{PP}, Y_{PO4}$	[34]
$\alpha_{XI}, i_{NXS}, i_{NXI}, K_{O2AUT}, K_{NH4AUT}, b_{AUT}, n_{NO3}, b_H, K_{NO3}, K_{O2}$	[35]

In addition to calibration with an experienced-based approach to determine EBPR under different phosphorus/acetate (P/HAc) ratios with the ASM2d modeling in the SBR performance, it has been shown that only  $\mu_{AUT}$  is necessary to calibrate  $NH_4$  and  $NO_3$  [33]. A practical identifiability approach for the ASM2d calibration is to select the parameter subset sizes for autotrophs with three calibrated parameters:  $b_{AUT}, K_{NH4}$  and  $\mu_{AUT}$  [5]. Another study [6] on activated sludge anaerobic/anoxic/oxic ( $A^2/O$ ) pilot WWTP using an identifiability approach with the Fisher Information Matrix (FIM) tool to reduce ASM2d parameter subset sizes used only  $\mu_{AUT}$ . This presents a calibrated autotroph parameter and the parameter subset size is  $b_{PAO}, Y_{PO4}, \mu_{AUT}$ . The calibrated parameters included in the simulation of nitrogen removal at the Hanover-Gümmerswald pilot wastewater treatment plant were  $\mu_{AUT}, \alpha_{XI}, n_{NO3HYD}, K_b, n_{Fe}, \mu_H, K_{O2}, n_{NO3}, K_{NH4AUT}, q_{PHA}, q_{PP},$  and  $Y_{PO4}$ . This was based on ASM2d and ASM3P model concepts [34]. This current study several parameters govern the fitting of the simulation to model to  $PO_4$  in anaerobic phase and effluent TP. Those parameters (TABLE IV) include:  $Y_{PAO}, Y_{PO4}, Y_{PHA}, q_{PHA}, q_{PP}, \mu_{PAO}, b_{PAO}, b_{PP}, b_{PHA},$  and  $K_{PS}$ . In another study [15],  $Y_{PAO}$  and  $Y_{PO4}$  calibrated parameters were used to investigate the effect of extra acetate on the anaerobic/aerobic/anoxic (AOA) processes for simultaneous nitrogen and phosphorus removal based on the ASM2d modeling with the additional denitrifying PAOs (DNPAOs) kinetics. That modeling has expressed the optimum concentration of supplementary COD and formulated the microorganism metabolism. Thus the application of that modeling to the different wastewater compositions, such as COD/N/P, can be conducive to predicting PAOs behavior [15]. To study phosphorus storage capacity-limiting and phosphorus loading-limiting conditions, there are 8 significant calibrated parameters including  $\mu_{AUT}, b_{PAO}, b_{PP}, b_{PHA}, q_{PHA}, q_{PP}, K_{PHA}$  and  $Y_{PO4}$  used for the predicted simulations of  $S_{PO4}, X_{PHA}, S_A$  and MLSS profiles in the sequencing batch reactor (SBR) performance for EBPR fed with acetate as the carbon sole carbon source under different P/HAc ratios [33]. The calibration and simulation of ASM2d model at different temperatures in a phosphorus removal pilot plant show that the significant calibrated parameters include  $Y_H, \mu_H, K_F, b_H, n_{NO3}, \mu_A, K_{NH4}, b_A, Y_{PO4}, q_{PHA}, K_A, Y_{PAO}, \mu_{PAO}, q_{PP}, b_{PAO}, K_{PHA}, K_{IPP},$  and  $K_{MAX}$  [12]. To simulate the  $O_2, COD, NH_4,$  and  $PO_4$  data sets in an activated sludge system, a large parameter set [35] was included  $\alpha_{XI}, i_{NXS}, i_{NXI}, K_{O2AUT}, K_{NH4AUT}, b_{AUT}, n_{NO3}, b_H, K_{NO3},$  and  $K_{O2}$ . Another study [8] included  $\mu_{AUT}, \alpha_{XI}, \alpha_{SA}, \alpha_{SF}, n_{NO3HYD}, K_{PHA}, \mu_{PAO}$ . If this methodology has been successful to calibrate the pilot plant operation. The expectation when using this in a full-scale site can reduce time consumption for calculation parameter subset sizes. Subsequently, operation processes can be enhanced on basis of understanding organism behaviors. However, fluctuation of wastewater characteristics and complexity of operation systems may cause calculation errors.

## IV. CONCLUSION

The reducing parameter subset to the ASM2d calibration has been addressed by evaluating a novel calibration approach. The parameter significant ranking showed that the parameters for PAOs were among the most influential parameters on the model outputs. The parameter sensitivity and the parameter subsets are related to data available for calibration. The new calibration analysis uses experimental results. This approach can enable researchers to reduce heavy computation demand and avoids the need to choose the modeling parameters. This is a simplified approach for practical use.

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