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วิธีการลดตัวแปร ASM2dในระบบการกำจัดฟอสฟอรัสทางชีวภาพ

An Approach to Reducing ASM2d Parameter Subsets in Biological Phosphorus Removal Processes

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บทคัดย่อ

กระบวนการทำคาลิเบรชั่นด้วยวิธีการใหม่ได้เสนอหลักการเพื่อลดจำนวนตัวแปรของโมเดล ASM2dตัวแปรที่ได้มีความสัมพันธ์สำหรับแต่ละกระบวนการบำบัดน้ำเสียตะกอนเร่งและช่วยลดความซับซ้อนสำหรับการประมวลผลด้วยโปรแกรมทางคณิตศาสตร์อาศัยเพียงหลักการเซนซิติวิตี้ และวิธีการอิเทเรชั่นจะได้ตัวแปรและค่าของตัวแปรนั้นๆกระบวนการคาลิเบรชั่นเริ่มจากการทำอิเทเรชั่นจากตัวแปรที่มีค่าเซนซิติวิตี้สูงสุดไปหาต่ำสุดจำนวนการทำอิเทเรชั่นสำหรับแต่ละผลการทดลองมีค่าเท่ากับจำนวนตัวแปรที่ได้จากการทำเซนซิติวิตี้ตัวแปรที่ได้สัมพันธ์กับผลทดลองและได้ค่าของตัวแปรจากการประมวลผลจากแบบจำลองซึ่งมีค่าใกล้เคียงกับค่าจากผลการทดลองมากที่สุดหลักการนี้สามารถนำไปประยุกต์ใช้สำหรับโมเดลอื่นๆ นำวิธีการนี้ไปประยุกต์ใช้เพื่อพิจารณาตัวแปรและค่าของตัวแปรในกระบวนการกำจัดฟอสฟอรัสในระบบตะกอนเร่งด้วยโมเดล ASM2dพบว่าประสบความสำเร็จตัวแปรที่ได้ประกอบด้วยY_{PAO}, Y_{PO4}, Y_{PHA}, q_{PHA}, q_{PP}, μ_{PAO}, b_{PAO}, b_{PP}, b_{PHA}, K_{PS}, Y_A, μ_{AUT}, b_{AUT}, $K_{O2\ AUT}$, และ $K_{NH4\ AUT}$

คำสำคัญ : การกำจัดฟอสฟอรัส; คาลิเบรชั่น; ตัวแปร;วิธีการอิเทเรชั่น; โมเดล ASM2d; เซนซิติวิตี้

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. The results of the simulation provide calibration parameters. These included Y_{PAO}, Y_{PO4}, Y_{PHA}, q_{PHA}, q_{PP}, μ_{PAO}, b_{PAO}, b_{PP}, b_{PHA}, K_{PS}, Y_A, μ_{AUT}, b_{AUT}, $K_{O2\ AUT}$, and $K_{NH4\ AUT}$.

Keywords :ASM2d; calibration approach;iteration methodology; parameter; phosphorous removal; sensitivity

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]. To study carbon, nitrogen and phosphorous 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 [2]. ASM2d can explain phosphorus utilization by phosphorus accumulating organisms (PAOs) under aerobic conditions as well as denitrification mechanisms of PAOs. However, the ASM2d model is complicated to calibrate. This is due to a requirement of large number the model parameters. These are most often derived from the information content of particular wastewater treatment plants (WWTPs) [3], [4].The Modified University of Cape Town (MUCT) processes have been widely used in activated sludge WWTPs for prevention of eutrophication [6]. Other researchers [1] 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 doing so 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 influence 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 [3], [4]. In contrast, the experience-based approach requires process knowledge of particular activated sludge unit operations to derive model parameters [5]. In using the experience based approach for this study, 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 [1]. 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 purpose of this research is to present a new calibration approach. The goal was toavoid both high calculation demands and the requirement for a priori knowledge of all the parameters specific to the activated sludge treatment works. This avoids high computational demand and reduces the size of ASM2d parameter subset.

Materials and Methods

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 (Figure 1) consisted of five reactors in series. They included anaerobic, 1st anoxic, 2nd 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 operatingconditions 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 rate (Q_1 = 60 L/h) and aerobic recirculation flow rate (Q_2 = 60 L/h). In order to develop EBPRprocesses, acetic acid was fed to influent. The experimental samples were observed on a daily basis for the influent, anaerobic andaerobic stages as well as for the effluent. Average process temperature was maintained at 17°C. The process was fed withmunicipal wastewater.

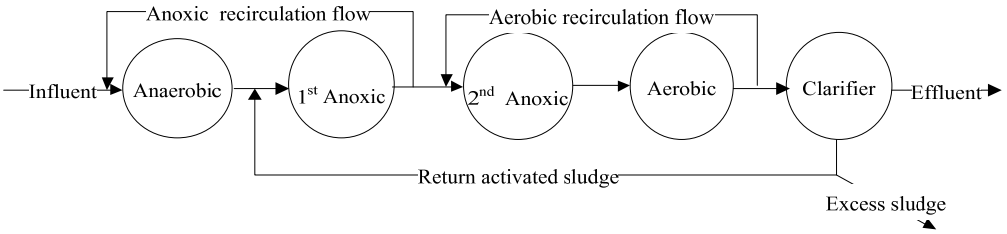


Figure 1 A schematic diagram of the activated sludge MUCT

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 [6]. 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:

$$s_{i,j} = \frac{\Delta\theta_j}{sc_i}\frac{\partial y_i}{\partial\theta_j}, \qquad \bar{s}_{i,j} = \frac{s_{i,j}}{\sqrt{\sum_{k=1}^{n} s^2_{k,j}}} \tag{1}$$

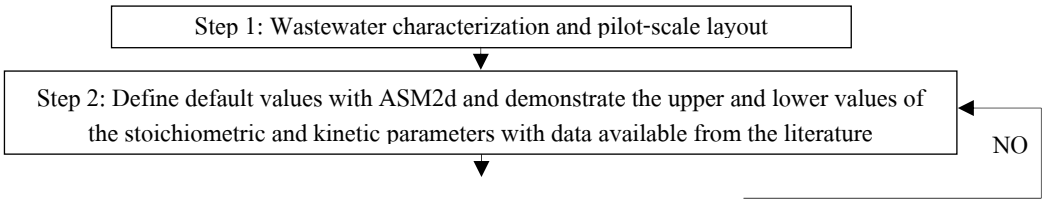
The matrices $S = (s_{i,j})$ and $\bar{S} = (\bar{s}_{i,j})$, and the column vectors $s_j = (s_{1,j}, \ldots, s_{n,j})^T$ and $\bar{s}_j = (\bar{s}_{1,j}, \ldots, \bar{s}_{n,j})^T$, where $\partial y_i / \partial\theta_j$ is the absolute sensitivity of the model output y to the parameter θ_j at a particular time. The matrices, S and $\bar{S}$, contain values of the various sensitive parameters. The vectors $\bar{s}_j$ are defined as normalization: $\bar{s}_j = s_j / \|s_j\|$. The $\Delta\theta_j$ value is the uncertainty range of the parameter θ_j according to prior knowledge which is classified into three uncertainty classes and sc_i is a

y_i

characteristic scale of the variable [3]. Aquasim[7]was used to calculate the sensitivity analysis.

Iteration methodology in the new calibration approach

Using all possible stoichiometric and kinetic parameters values in model would prevent calibration accuracy [3]. Such calculations would require a very long time. Additionally, round off and truncation errors may be introduced and grow during the calculations. This approach, therefore, employed the used of parameter subsets. Sensitivity parameter functions were used in the implementation iteration withAquasim [7]. The procedures for that iteration calibration are shown in Figure 2. A stepwise manualiteration methodologywas specificallyadapted to EBPRin whichthe simulationresultswere calibrated usingobserved results with the parameter significance ranking in order to achieve a reasonable model fit. The iterative algorithm wasreevaluated until refinement of the sensitivity parameters no longer affected the simulation output.



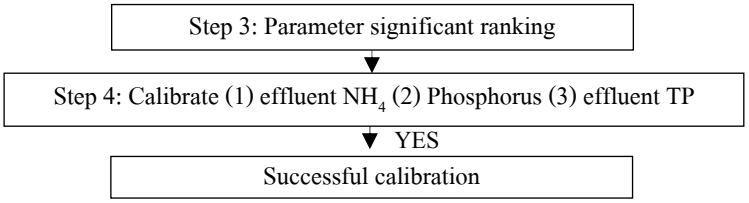


Figure 2 A new calibration approach procedures to reducing ASM2d parameter subsets

Results and Discussion

Step 1: Influent wastewater characteristics

The simulation of operating period was completed for a steady state processes. The influent characteristics are summarized in Table 1.

Table 1 Characterization of influent wastewater components

Symbol	Definition	Influent	Unit	Reference
S_{O2in}	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_{Iin}	Inert soluble organic substrates	53.50	g COD/ m^3	This study
S_{NH4in}	Ammonium	33.53	g N/m^3	This study
S_{NO3in}	Nitrate (plus nitrite)	0	g N/m^{-3}	This study
S_{PO4in}	Phosphate	5.04	g P/m^3	This study
S_{N2in}	Dinitrogen (N_2) , 0.78 atm at 20 ºC	0	g N/m^3	This study
X_{Iin}	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, PAOs	0	g COD/m^3	[1]
X_{PPin}	Stored poly-phosphate of PAOs	0	g P/m^3	[1]
X_{PHAin}	Organic storage products of PAOs	0	g COD/m^3	[1]

Step 2: 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 stoichiometric and kinetics parameters of phosphorus accumulating organisms (PAOs). Maximum and minimum values for these parameters are given in Table 2.

Table2 Default, minimum and maximum values for parameters involved on ASM2d

Symbol	Definition	Default	Min.	Max.	Unit	References
Y_{PO4}	Poly-phosphate (PP) requirement (PO_4/PHA)	0.40	0.26	0.46	g P/g COD	[2],[5],[10],[11],[13],[16]
Y_{PAO}	Yield coefficient (Biomass/PHA)	0.625	0.58	0.90	g COD/g COD	[2],[11],[16]
q_{PHA}	Rate constant for storage of X_{PHA}	3.00	0.36	9.03	g X_{PHA}/g X_{PAO}/d	[2],[5],[8],[9],[10],[11],[13],[16]
q_{PP}	Rate constant for storage of X_{PP}	1.50	1.00	10.88	g X_{PP}/g X_{PAO}/d	[2],[5],[10],[11],[13],[16]
μ_{PAO}	Maximum growth rate of PAOs	1.00	0.67	2.97	d^{-1}	[2],[5],[9],[10],[13],[16]
η_{NO3}	Reduction factor for anoxic activity	0.60	0.44	0.60		[2],[5]
b_{PAO}	Rate for Lysis of X_{PAO}	0.20	0.04	0.27	d^{-1}	[2],[5],[9],[10],[11],[12],[16]
b_{PP}	Rate for Lysis of X_{PP}	0.20	0.03	0.20	d^{-1}	[2],[5],[11],[16]
b_{PHA}	Rate for Lysis of X_{PHA}	0.20	0.08	0.20	d^{-1}	[2],[16]

K_{O2}	Saturation/inhibition coefficient for oxygen	0.20	0.20	0.20	g O_2/m^3	[2],[16]
K_{NO3}	Saturation coefficient for nitrate, S_{NO3}	0.50	0.50	0.50	g N/m^3	[2],[5],[8],[10],[16]
K_A	Saturation coefficient for acetate, S_A	4.00	1.00	32.00	g COD/m^3	[2],[5],[11],[16]
K_{NH4}	Saturation coefficient for ammonium (nutrient)	0.05	0.01	0.05	g N/m^3	[2],[13],[16]
K_{PS}	Saturation coefficient for P in storage of PP	0.20	0.20	0.50	g P/m^3	[2],[11],[16]

Table 2 (cont.)Default, minimum and maximum values for parameters involved on ASM2d

Symbol	Definition	Default	Min.	Max.	Unit	References
K_P	Saturation coefficient for phosphate (nutrient)	0.01	0.01	3.00	g P/m^3	[2],[8],[12],[16]
K_{ALK}	Saturation coefficient for alkalinity (HCO_3)	0.10	0.02	0.10	mole	[2],[16]
K_{MAX}	Maximum ratio of X_{PP}/X_{PAO}	0.34	0.152	0.37	g X_{PP}/g X_{PAO}	[2],[5],[10],[16]
K_{PP}	Saturation coefficient for poly-phosphate	0.01	0.01	0.26	g X_{PP}/g X_{PAO}	[2],[8],[16]
K_{IPP}	Inhibition coefficient for PP storage	0.02	0.001	0.48	g X_{PP}/g X_{PAO}	[2],[5],[10],[16]
K_{PHA}	Saturation coefficient for PHA	0.01	0.001	0.01	g X_{PHA}/g	[2],[5],[9],[10],[16]
$K_{O2\ AUT}$	Saturation coefficient for oxygen	0.50	0.10	1.00	g O_2/m^3	[2],[11]
$K_{NH4\ AUT}$	Saturation coefficient for ammonium (substrate)	1.00	0.30		g N/m^3	[2],[11]

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 werethe most significant of the data inputs, i.e., when the rootsof mean squared values of sensitivities werehigher than 0. From this, the parameter subsets under these studies were reduced to the top 30 as shownin Table 3. Consequently, the resulting 30 parameters were used to for calibration in analyzing all experimental results. 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 particular WWTP configurations and operation, and some properties of collected data [1].In this study, ASM2d was calibrated using an identifiability method to describe nitrogen and phosphorus removal in the Haaren (The Netherlands) WWTP [1]. In anotherapplication, this approach to ASM2d calibration used an identifiability analysis in a systematic manner [3]. PAOs play an important role in the dynamics of the EBPR processes. It was applied to EBPR ata full scale WWTP in Switzerland [3]. Additionally, to calibrate ASM2d for anaerobic/anoxic/oxic conditions (A2/O), a pilot WWTP used an identifiability approach [4]. PAOs parameters were also among the most sensitivity. The parameter significancerankings used an identifiability approach [4]. PAOs parameters were also among the most sensitivity. The parameter significancerankings ofthecurrent study are different from that of other researchers [1], [3], [4]. 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^{th}[4], 15^{th}[1], and it was excluded altogether in another study [3].Also researchers [3] found that parameter b_{PAO} had the highest sensitivity although itranked 4^{th} and 27^{th} in other studies [1], [4]. This parameter's sensitivity was ranked lower in the current study (29^{th}). Considering the second most significant sensitivity ranking in this study, μ_{PAO}, it was of the same order as in one study [3], but it was at a

Table 3 The ASM2d parameter significance ranking with roots of mean squared (RMS) of sensitivities

Ranking	Parameter	RMS	Ranking	Parameter	RMS	Ranking	Parameter	RMS
1	Y_{PO4}	26.43	11	b_{PHA}	2.16	21	f_{XI}	0.07
2	μ_{PAO}	23.45	12	Y_A	1.59	22	K_{PHA}	0.04
3	Y_{PAO}	19.51	13	K_{IPP}	1.29	23	K_{NO3}	0.03
4	q_{PP}	18.35	14	μ_H	1.11	24	K_F	0.02
5	$K_{O2\ AUT}$	18.01	15	η_{NO3}	1.01	25	K_h	0.02

6	$K_{NH4\ AUT}$	11.85	16	q_{PHA}	0.94	26	K_X	0.01
7	b_{PP}	8.93	17	K_{PS}	0.53	27	K_P	0.01
8	μ_{AUT}	7.99	18	K_{PP}	0.47	28	q_{fe}	0.01
9	Y_{PHA}	4.76	19	K_{AUT}	0.23	29	b_{PAO}	0.01
10	b_{AUT}	2.76	20	$K_{ALK\ PAO}$	0.22	30	Y_H	0.01

lower position (17^{th}) in other work [1], [4]. Additionally, the current study found that μ_{AUT} had a higher sensitivity ranking than other studies [1], [3]. However, its ranking was lower than reported elsewhere [4]. Furthermore the sensitivity analysis in other work [6] used only two parameters, Y_{PAO} and Y_{PO4}. One group of researchers [14]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.

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 effluentand 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 first. This was followed by each of the other 29parameters included in the parameter significance ranking in order of decreasing influence. Iterations begun with the initialdefault parameter value and were carried out under the steady stateconditions. 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 4. As aresult of fitting the simulated data to the effluent NH_4 concentration, it was found that there are five significant parameters. They are: Y_A, the maximum growth rate for autotrophs(μ_{AUT}), the decay rate of X_{AUT} (b_{AUT}),$K_{NH4\ AUT}$, $K_{O2\ AUT}$.Both Y_A and $K_{O2\ AUT}$ were the same as their default values. Comparison of the parameter subsets to other experiments using different protocols is shown inTable 5. Significant parameters based upon NH_4 in effluent using the experienced-based approach for the experiments of sequencing batch reactors (SBRs) [13] were calibrated. To accomplish this, nutrients were removed under limited aeration conditions. The parameters examined included μ_{AUT} and K_{NH4}. In addition to calibration with an experienced-based approach todetermine EBPR under different phosphorus/acetate (P/HAc) ratios with the ASM2d modeling in the SBR performance, it hasbeen shown that only μ_{AUT} isnecessary to calibrate NH_4 and NO_3[14]. A practical identifiability approach for the ASM2dcalibration is to select the parameter subset sizes for autotrophs with three calibrated parameters: b_{AUT}, K_{NH4} and μ_{AUT}[3]. Anotherstudy [4] on activated sludgeanaerobic/anoxic/oxic (A^2/O) pilot WWTPs using an identifiability approach with the Fisher

Table 4 The values of the calibrated ASM2d parameters

Symbol	Unit	ASM2d	Calibrated value	Symbol	Unit	ASM2d	Calibrated value
Y_{PAO}	g COD/g	0.625	0.60	b_{PHA}	d^{-1}	0.20	0.20
Y_{PO4}	g P/g COD	0.40	0.40	K_{PS}	g P/m^3	0.20	0.35
Y_{PHA}	g COD/g P	0.20	0.23	Y_A	g COD/g N	0.24	0.24
q_{PHA}	g X_{PHA}/g	3.00	3.50	μ_{AUT}	d^{-1}	1.00	1.20

q_{PP}	g X_{PP}/g	1.50	1.50	b_{AUT}	d^{-1}	0.15	0.05
μ_{PAO}	d^{-1}	1.00	1.00	$K_{O2\ AUT}$	g O_2/m^3	0.50	0.50
b_{PAO}	d^{-1}	0.20	0.20	$K_{NH4\ AUT}$	g N/m^3	1.00	0.15
b_{PP}	d^{-1}	0.20	0.20				

Table 5 The parameter subsets in different studies

Parameter subsets	Reference
Y_{PAO}, Y_{PO4}, Y_{PHA}, q_{PHA}, q_{PP}, μ_{PAO}, b_{PAO}, b_{PP}, b_{PHA}, K_{PS}, Y_A, μ_{AUT}, b_{AUT}, $K_{O2\ AUT}$, $K_{NH4\ AUT}$	This study
b_{PAO}, μ_{PAO}, q_{PHA}, q_{PP}, b_{PP}, K_h, η_g, b_{AUT}, K_{NH4}, μ_{AUT}	[3]
b_{PAO}, Y_{PO4}, μ_{AUT}	[4]
Y_{PAO}, Y_{PO4}	[6]
μ_{AUT}, K_{NH4}, K_X, K_N, K_O, K_{OA}, Y_{HNO3}, b_H, Y_{PO4}, q_{PHA}, μ_{PAO}, q_{PP}	[13]
μ_{AUT}, b_{PAO}, b_{PP}, b_{PHA}, q_{PHA}, q_{PP}, K_{PHA}, Y_{PO4}	[14]
μ_{AUT}, $\eta_{NO3\ HYD}$, K_h, η_{fe}, μ_H, K_{O2}, η_{NO3}, $K_{NH4\ AUT}$, q_{PHA}, q_{PP}, Y_{PO4}	[15]
i_{NXS}, i_{NXI}, K_{O2AUT}, $K_{NH4\ AUT}$, b_{AUT}, η_{NO3}, b_H, K_{NO3}, K_{O2}	[17]

Information Matrix (FIM) tool to reduce ASM2d parameter subset sizes used only μ_{AUT}.This presents a calibrated autotrophparameter and the parameter subset size is b_{PAO}, Y_{PO4}, μ_{AUT}. The calibratedparameters included in the simulation ofnitrogenremoval at the Hanover-Gümmerwald pilot wastewater treatment plant were μ_{AUT}, $\eta_{NO3\ HYD}$, K_h, η_{fe}, μ_H, K_{O2}, η_{NO3}, $K_{NH4\ AUT}$, q_{PHA}, q_{PP}, and Y_{PO4}. This was based on ASM2d and ASM3P model concepts [15]. This current study severalparameters govern the fitting of the simulation to model to PO_4 in anaerobic phase and effluent TP. Those parameters (Table 4) include: Y_{PAO}, Y_{PO4}, Y_{PHA}, q_{PHA}, q_{PP}, μ_{PAO}, b_{PAO}, b_{PP}, b_{PHA}, and K_{PS}. This methodology wassuccessful to calibrate the pilot plant operation. In another study [6], 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 removalbased on the ASM2d modeling with the additional denitrifying PAOs (DNPAOs)kinetics. To study phosphorus storage capacity-limiting and phosphorus loading-limiting conditions, there are 8 significant calibrated parameters including μ_{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 [14].To simulate the O_2, COD, NH_4, and PO_4 data sets in an activated sludge system, a large parameter set [17] was included i_{NXS}, i_{NXI}, K_{O2AUT}, $K_{NH4\ AUT}$, b_{AUT}, η_{NO3}, b_H,K_{NO3}, and K_{O2}.

Conclusions

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 expectation when using this in a full-scale site is that its use can reduce time required for calculation of parameter subset sizes. Subsequently, operation processes can be enhanced on basis of understandingorganism behaviors. This is a simplified approach for practical use.However, fluctuation of wastewater characteristics and complexity of operation systems may cause calculation errors.

Acknowledgements

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