World Academy of Science, Engineering and Technology
International Journal of Environmental and Ecological Engineering
Vol:6, No:4, 2012

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_{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 $K_{NH4\ AUT}$. 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 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 forpreventionof 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].

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Other researchers [2] reported that the model is over-parameterized due to the paucity ofexperimental 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 successfullyattain modeling calibration.Each achieves values for the necessary stoichiometric and kinetic parameters and satisfiesthe 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 reducethe number of iterations required.It furtherrepresents 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 calculationdemands and the requirement for a priori knowledge of all theparameters specific to the activated sludge treatment works.

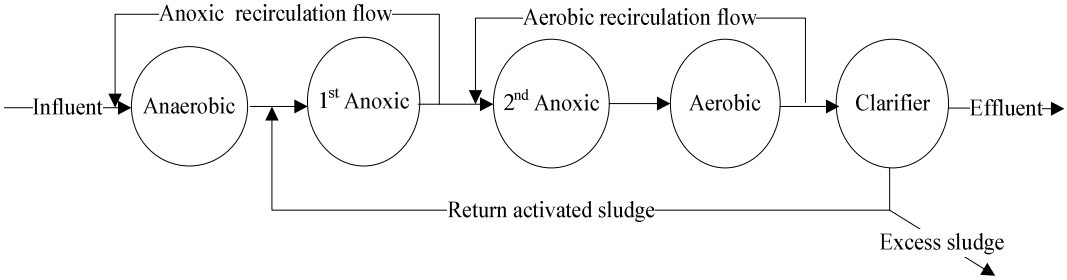

Fig. 1 A schematic diagram of the activated sludge MUCT

This new method was developed using the identifiabilityapproach and the experience-based approach. The sensitivitymethod 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, 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 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:

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

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

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

where $\partial y_i/\partial \theta_j$ is the absolute sensitivity of the model output *y* to the parameter θ_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: $\tilde{s}_j = s_j/\|\tilde{s}_j\|$. 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 andsc_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 beintroduced and grow during the calculations. Our approach,therefore, employed the used of parameter subsets.

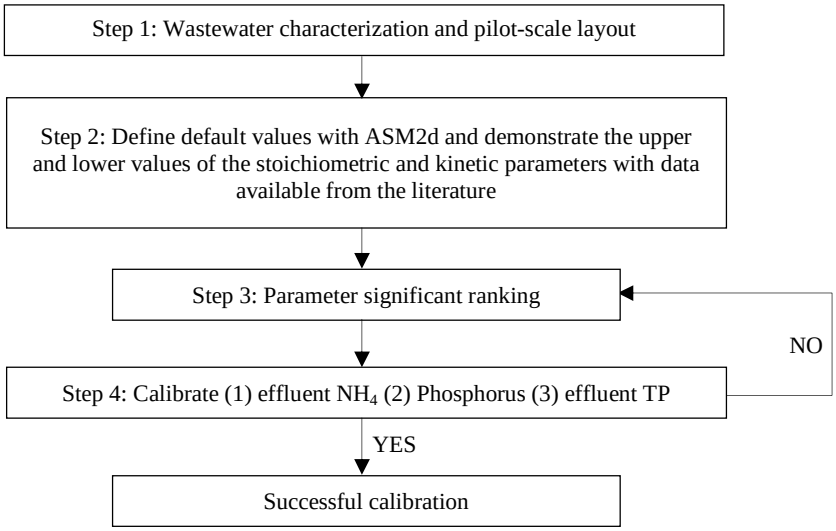

Fig. 2 A new calibration approach procedures to reducing ASM2d parameter subsets

Someparameters 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 theimplementation 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 completedfor 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_{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, 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_{PO4}	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]
μ_{PAO}	Maximum growth rate of PAO	1.00	0.67	2.97	d^{-1}	[3], [25], [26], [28], [29], [36]
η_{NO3}	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^{-1}	[3], [24], [25], [26], [27], [28], [29], [36]
b_{PP}	Rate for Lysis of X_{PP}	0.20	0.03	0.20	d^{-1}	[3], [24], [26], [27]
b_{PHA}	Rate for Lysis of X_{PHA}	0.20	0.08	0.20	d^{-1}	[3], [26], [28], [36]
K_{O2}	Saturation/inhibition coefficient for oxygen	0.20	0.20	0.20	g O_2/m^3	[3], [36]
K_{NO3}	Saturation coefficient for nitrate, S_{NO3}	0.50	0.50	0.50	g N/m^3	[3], [36]
K_A	Saturation coefficient for acetate, S_A	4.00	1.00	32.00	g COD/m^3	[3], [25], [28], [29], [36], [23]
K_{NH4}	Saturation coefficient for ammonium (nutrient)	0.05	0.01	0.05	g N/m^3	[3], [31], [36]
K_{PS}	Saturation coefficient for phosphorus in storage of PP	0.20	0.20	0.50	g P/m^3	[3], [26], [36]
K_P	Saturation coefficient for phosphate (nutrient)	0.01	0.01	3.00	g P/m3	[3], [23], [27], [36]
K_{ALK}	Saturation coefficient for alkalinity (HCO_3)	0.10	0.02	0.10	mole HCO_3/m^3	[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						
$K_{O2\ AUT}$	Saturation coefficient for oxygen	0.5	0.1	1.0	g O_2/m^3	[26]
$K_{NH4\ AUT}$	Saturation coefficient for ammonium (substrate)	1.00	0.3		g N/m^3	[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 werethe most significant of the data inputs, ie, when therootsof mean squared values of sensitivities were higher than 0. From this, the parameter subsets under these studies were reduced to the top 30 as shownin TABLE III**.** Consequently, the resulting 30 parameters were used to calibration in analyzing allexperimental results. Other researchers [7] have usedsensitivity parameter rankingswith roots of mean squared values larger than 0.2 and found 11 relevant parameters thatwere used to calibrate the Activated Sludge Model No. 1(ASM1) applied to full-scale plant data. Differences inparameter 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	μ_{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	μ_{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	μ_H	1.11
15	η_{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 someproperties of collected data [2].Theparameter significance ranking showed that temperature correction coefficients andthe 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 significancerankings 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 8th [6], 15th [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 4th and 27th in other studies [6], [2]. This parameter's sensitivity was ranked lower in the current study (29th). Considering the second most significant sensitivity ranking in this study,μ_{PAO}, it was of the same order as in one study [5], but it was at a lower position (17th) in other work [2], [6]. Additionally, the current study found thatμ_{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 needingextensive 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 significantparameter was iterated. This was followed byeach of the other 29 parametersincluded in the parameter significance ranking inorder of decreasing influence. Iterations begun with the initial defaultparameter 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 theNH_4experiments 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 maximumgrowth rate for autotrophs (μ_{AUT}), the decay rate of X_{AUT} (b_{AUT}), saturation coefficient for oxygen ($K_{O2\ AUT}$), nitrogen half saturation coefficient for autotrophs ($K_{NH4\ AUT}$). μ_{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
μ_{PAO}	1.0	1.0	d^{-1}
b_{PAO}	0.2	0.2	d^{-1}
b_{PP}	0.2	0.2	d^{-1}
b_{PHA}	0.2	0.2	d^{-1}
K_{PS}	0.2	0.35	g P/m^3
Autotrophs			
Y_A	0.24	0.24	g COD/g N
μ_{AUT}	1.0	1.2	d^{-1}
b_{AUT}	0.15	0.05	d^{-1}
$K_{O2\ AUT}$	0.5	0.5	g O_2/m^3
$K_{NH4\ AUT}$	1.00	0.15	g N/m^3

Next b_{AUT} was decreased in relation to increasing autotrophic growth rate. Later $K_{NH4\ AUT}$ decreased because of low ammonium concentration in the aerobic phase.Both Y_A and $K_{O2\ AUT}$ 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 μ_{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}, 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_{fe}, b_{AUT}, K_{NH4}, μ_{AUT}	[5]
b_{PAO}, Y_{PO4}, μ_{AUT}	[6]
μ_{AUT}, α_{XI}, α_{SA}, α_{SF}, $\eta_{NO3\ HYD}$, K_{PHA}, μ_{PAO}	[8]
Y_H, μ_H, K_F,b_H, η_{NO3}, μ_A, K_{NH4}, b_A, Y_{PO4}, q_{PHA}, K_A, Y_{PAO}, μ_{PAO}, q_{PP}, b_{PAO}, K_{PHA}, K_{IPP}, K_{MAX},	[12]
Y_{PAO}, Y_{PO4}	[15]
μ_{AUT}, K_{NH4}, K_X, K_N, K_O, K_{OA}, Y_{HNO3}, b_H, Y_{PO4}, q_{PHA}, μ_{PAO}, q_{PP}	[31]
μ_{AUT}, b_{PAO}, b_{PP}, b_{PHA}, q_{PHA}, q_{PP}, K_{PHA}, Y_{PO4}	[33]
μ_{AUT}, α_{XI}, $\eta_{NO3\ HYD}$, K_h, η_{fe}, μ_H, K_{O2}, η_{NO3}, $K_{NH4\ AUT}$, q_{PHA}, q_{PP}, Y_{PO4}	[34]
α_{XI}, i_{NXS}, i_{NXI}, K_{O2AUT}, $K_{NH4\ AUT}$, b_{AUT}, η_{NO3}, b_H,K_{NO3}, K_{O2}	[35]

In addition to calibration with an experienced-based approach to determine EBPR underdifferent phosphorus/acetate (P/HAc) ratios with the ASM2d modeling in the SBR performance, it has been shown that only μ_{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 autotrophswith three calibrated parameters: b_{AUT}, K_{NH4} and μ_{AUT}[5].Another study [6] on activated sludgeanaerobic/anoxic/oxic (A^2/O) pilot WWTPsusingan identifiability approach with the Fisher Information Matrix (FIM) tool to reduce ASM2d parameter subset sizes used onlyμ_{AUT}. This presents a calibrated autotroph parameter and the parameter subset size is b_{PAO}, Y_{PO4}, μ_{AUT}. The calibratedparameters included in the simulation of nitrogen removal at the Hanover-Gümmerwald pilot wastewater treatment plant were μ_{AUT}, α_{XI}, $\eta_{NO3\ HYD}$, 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 [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}, μ_{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 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 [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, μ_H, K_F,b_H, η_{NO3}, μ_A, K_{NH4}, b_A, Y_{PO4}, q_{PHA}, K_A, Y_{PAO}, μ_{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 α_{XI}, i_{NXS}, i_{NXI}, K_{O2AUT}, $K_{NH4\ AUT}$, b_{AUT}, η_{NO3}, b_H,K_{NO3}, and K_{O2}. Another study [8] included μ_{AUT}, α_{XI}, α_{SA}, α_{SF}, $\eta_{NO3\ HYD}$, K_{PHA}, μ_{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 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.

Acknowledgement

The work was fully supported by the Thai government and Suranaree University of Technology, Thailand.

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