Simplifications of Activated Sludge Model with preservation of its dynamic accuracy

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Abstract: The complexity of ASM1 model is a major obstacle for their effective use in control and monitoring algorithms. In wastewater treatment plants, the effluent is in addition subjected to hydrodynamic phenomena which enhance the model complexity. The aim of model reduction is to circumvent this problem by eliminating parts of a model that are unimportant for dynamic model accuracy. In this study different ways to simplify ASM1 model simulated in BSM1 conditions are presented. The method is based on physical considerations that are analyzed separately. The simplifications finally provide really important loss of accuracy on compounds of interest, highlighting the lack of relevant simplified model.

Keywords: Water pollution, Activated Sludge Processes, ASM1 model, Reduced-order models

1. INTRODUCTION

The Activated Sludge Model n°1 (ASM1), established by the International Water Association, is destined to promote and facilitate the practical methods of designing and operating the biological treatment systems for wastewater systems (Henze *et al.*, 2000). A Benchmark (Copp, 1999) has been proposed by the European program COST 624 for the evaluation of control strategies in wastewater treatment plants. The Benchmark is based on the most common wastewater treatment plant: a continuous flow activated sludge plant performing nitrification and pre-nitrification.

For activated sludge processes, a simulation model is a need to avoid numerous tests which lead to operating conditions that may be difficult or even impossible to realize. Concerning automatic control, a simple model, non-representative of all the dynamics of the process, may be sufficient (Jeppsson, 1996). However, the more important the domain of validity is, the more efficient the control law will be. In case of process monitoring, diagnosis or even fault tolerant control, process dynamics must be very well known and anticipated. In (Hauduc *et al.*, 2009) it is shown that the ASM1/BSM1 models are not directly used, but simplified before use.

The complexity of modeling activated sludge processes is of two kinds: the biological behavior, for which the state-of-art is the ASM1 model, and the hydrodynamic phenomena which enhance the model complexity. To obtain a manageable model, several approaches may be used: systematic method of simplification (i.e. singular perturbation method), knowledge on a specific process or building of a new model. These methods may be combined, leading to a wide variety of simplified models.

Whatever the model is, its validation involves difficulties that are specific to biological processes (Holmberg and Ranta, 1982). These difficulties may lead to influence some choices in the model simplification so as to make this task easier. Nevertheless, parametric identification and model validation are not addressed in this paper.

As the choice of reduction type is also influenced by the objective of the reduction, no single method is therefore superior in all cases. This paper considers each possible simplification from the dynamic accuracy point of view.

2. THE ASM1 MODEL AND THE BENCHMARK BSM1

The ASM1 model is able to represent the behavior of an urban effluent, loaded in nitrogen and carbon compounds. In order to estimate the organic pollution to be treated, the measurement of Chemical Oxygen Demand (COD) is used, though the information is not direct. The organic matter is fractioned according to physic-chemical criteria (particulate or soluble matter) and biodegradability (Fig. 1). Soluble compounds are noted "S" and particulate ones are noted "X".

Soluble COD	Inert organic matter S ₁ Readily biodegradable substrate S _S
Particulate COD	Inert organic matter X _I Slowly biodegradable substrate X _S Active heterotrophic biomass X _{BH} Active autotrophic biomass X _{BA}
	Particles arising from biomass decay X _P

Fig.1.Organic matter partitioning in ASM1 state variables Nitrogen is equally divided into four state variables: nitrate and nitrite nitrogen (S_{NO}), NH $_4^+$ and NH₃ nitrogen (S_{NH}), soluble (S_{ND}) and particulate (X_{ND}) biodegradable organic nitrogen. These nitrogen compounds are easily characterized by usual chemical analyses. Lastly, the model includes dissolved oxygen (S_0) and alkalinity (S_{ALK}).

The eight reaction rates of the model are:

- Biomass growth: aerobic growth of heterotrophic biomass by oxidation of organic matter (ρ_1); anoxic growth of heterotrophic biomass by denitrification reaction (ρ_2) and aerobic growth of autotrophic biomass by nitrification reaction (ρ_3),
- Decay of heterotrophic (ρ_4) and autotrophic (ρ_5) biomasses,
- Ammonification of soluble organic nitrogen (ρ_6),
- Hydrolysis of particulate organic matter (nitrogenous ρ_7 , carbonaceous ρ_8).

The reaction rates (ρ) are represented with Monod laws:

 $\rho = \mu.X$ (1) For ρ_1 , ρ_2 and ρ_3 : $\mu = \mu_{max} \cdot \prod_i \frac{[substrate]_i}{K_i + [substrate]_i} \mu(S_O)$ $\mu(S_O) = \frac{S_O}{K_{OH} + S_O} (aerobic) \quad \text{or} \quad \mu(S_O) = \frac{K_{OH}}{K_{OH} + S_O} (anoxic)$ For ρ_7 and ρ_8 : $\mu = \mu_{max} \left[\prod_i \frac{[substrate]_i}{K_i + [substrate]_i} \frac{S_O}{K_{OH} + S_O} + \prod_j \frac{[substrate]_j}{K_j + [substrate]_j} \frac{K_{OH}}{K_{OH} + S_O} \right]$

X is the biomass state variable (X_{BH} or X_{BA}), μ is the growth rate parameter (d⁻¹), μ_{max} is the maximal growth rate parameter (d⁻¹), K_i is the half-saturation coefficient for the considered substrate (g_{COD}.m⁻³), [substrate] is a substrate state variable. The term $\mu(S_O)$ expresses the oxygen conditions: aerobic or anoxic.

The model is established by mass balances characterizing the evolution of micro-organisms. The reaction rates include 6 growth rates parameters and 8 half-saturation coefficients: The 4 pseudo-stoichiometric coefficients represent the conversion rate of compounds.



Fig. 2 BSM1 plant

This benchmark BSM1 consists of a fully specified model of an activated sludge plant. The plant (Fig. 2) consists of a bioreactor, virtually separated in 5 fully mixed compartments and a secondary settler. The first two compartments are not aerated whereas the last three are aerated. The secondary settler is modeled as a series of 10 layers (one-dimensional model based on Takàcs model (Takàcs *et al.*, 1991). The complete description of the plant can be found in (Copp, 2002).

All in all, the ASM1 model is composed of 13 state variables, 8 kinetics and 18 parameters. Taking into account the hydrodynamic configuration, ASM1 is used 5 times (one by compartment) to obtain the BSM1 model which is the biological reactor model. The BSM1 model outputs must be gathered into soluble and particular compounds for the clarifier model.

In order to study the dynamic behavior of the process, a data base representative of the real plant behavior is proposed: the effluent compounds and the input flow are fluctuating similarly according to daily fluctuations, weekly ones and also weather conditions. Three data files are available: dry, rain and storm weather files.

3. MODEL SIMPLIFICATION

3.1 Singular perturbation method

The singular perturbation method is a rigorous method maintaining the nonlinear properties, and thus a larger validity domain. (Steffens, 1997), (Chachuat, 2001) and (Mulas, 2006) have used a systematic tool for partitioning. However simplifications must be validated by the user and the tool uses the linearized model, which diminishes the interest of the method. Referring to quasi-steady-state assumption (QSSA) approaches (Weijers, 2000), (Cadet *et al.*, 2004) have proposed an approach based on kinetic scaling, which lead to a solution which matches already known behavior of compounds.

Drawbacks are that the reduce model remains relatively complex and as the hydrodynamics is not taken into account, the reduce model ultimately offers few advantages compared to original model. Some interesting results should be however obtained if the clarifier is included in the model to be simplified, and if some more efficient methods for solving singular perturbations are used (Kumar and Parul, 2011).

3.2 Removal of non-reactional state variables

The thirteen state variables of the ASM1 model are not all biologically reactive. Thus alkalinity which is independent from other state variables and which is more precisely a measurement can be removed. The soluble inert components (S_I) and the particulate inert components (X_I) are not used in biological reactions. Furthermore, the state variable X_{P} , produced from the decay of biomass, is a biologically stable component, that may also be eliminated. These simplifications have been often used in literature (Mulas, 2006) (Chachuat, 2001) and thus remain 9 state variables per compartment.

It should however be kept in mind that these state variables are essential both for the clarifier model and for BSM1 model validation, as they provide the link with the COD measurements. In particular, situations where COD partition is fluctuating are not covered by the BSM1 model. In compounds addition, particulate fluctuate with hydrodynamics and their dynamical accuracy depends also on the clarifier model accuracy. The disadvantage is that the clarifier model is based on the assumption that the clarifier is in an equilibrated state at each instant. Indeed, the lack of clarifier model efficiency is a real bottleneck to the dynamical representativeness of the BSM1 model.

3.3 Hydrodynamic considerations

Most literature studies assimilate hydrodynamics to a perfectly mixed reactor subjected to prolonged aeration with separated decantation as (Chachuat 2001) and (Mulas 2006). Others (Vanrolleghem et al., 1999), (Fibrianto et al., 2008) and (Gómez-Quintero et al., 2000) use a laboratory pilot plant of Sequencing Batch reactor (SBR) type, allowing separation between the biological and the hydrodynamic phenomena. However, in the case of real activated sludge wastewater treatment plants, hydrodynamics can't be dismissed. (Alex et al., 1999) consider that hydrodynamics phenomena play a major role in the dynamic accuracy. (Pons and Potier, 2004) studied the effect of hydrodynamic increase complexity: perfectly mixed reactors in serial, plug flow reactor, axial dispersion. They concluded that the Benchmark configuration is sufficient to initiate a study, but that the real hydrodynamic behavior will have to be more precisely evaluated for a real application.

Conversely, the benchmark serial tanks may be simplified into two perfectly mixed reactors: one anoxic reactor and one aerobic reactor. Parameter estimation has been conducted, and has led to adjust only the transfer coefficient of oxygen. To estimate the residual error due to the simplifications, the mean of relative error and the root of the mean square error have been evaluated.

The mean of the absolute value of the relative error between the state variable vector with the simplified hydrodynamics (Z) and the BSM1 model (Z^{BSM1}) is:

$$E_{r}(j) = \frac{1}{n} \sum_{i=1}^{n} \frac{\left| Z(i,j) - Z^{BSM 1}(i,j) \right|}{Z^{BSM 1}(i,j)} \qquad j = 1:9$$
(2)

j represents the number of state variables and n is the number of measurements,

The root of the mean square error is:

$$\sigma(j) = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (Z(i, j) - Z^{BSM-1}(i, j))^2} \quad j = 1:9$$
(3)

Table 1. Error due to hydrodynamic simplifications

	Anoxic pha	ase	Aerobic phase	
	Er	σ	Er	σ
S_S (g _{COD} .m ⁻³)	38.8%	0.8	9.7%	0.1
X_S (g _{COD} .m ⁻³)	3.0%	2.6	8.4%	5.02
X_{BH} (g _{COD} .m ⁻³)	0.34%	11.8	0.4%	16.1
X_{BA} (g _{COD} .m ⁻³)	0.38%	0.66	0.5%	0.91
S_0 (g ₀₂ .m ⁻³)	-*	0.01	156%	0.74
S_{NO} (g _N .m ⁻³)	43.7%	0.37	5.3%	0.45
$S_{\rm NH}~(g_{\rm N.}m^{-3})$	2.75%	0.3	38.8%	0.58
S_{ND} (g _N .m ⁻³)	18.2%	0.17	8.2%	0.07
$X_{ND} (g_{N.}m^{-3})$	2.2%	0.13	6.2%	0.27

* As anoxic phase is very poor in oxygen content, result is not significant.

Table 1 shows that the results are globally good. However, if biomasses are the compounds the less affected, some are really affected by the simplification:

- Ss state variable in anoxic phase for carbonaceous,
- S_{NO} and S_{ND} in anoxic phase; S_{NH} in aerobic phase for nitrogen compounds, which is coherent with (Pons & Potier, 2004),
- Dissolved oxygen in aerobic phase (S_0)

The state variables S_{NO} , S_O and S_{NH} as they are easily measured are a usually used as a measurement for either estimating unmeasured compounds or use in an automatic control loop. Their bad dynamical representativeness is a problem to get information on the biological activity of the process. Thus, hydrodynamics may be simplified in a first approach, but has to be carefully studied in a real treatment plant.

3.4 Linearization of Monod Laws

Biological rates constitute the nonlinear terms of the ASM1 model. Linearizing them would lead to a linear model, which has been proposed by (Smets *et al.*, 2003). Here, only Monod laws linearization are concerned, which is only part of the linearization. Nevertheless, as the saturation of rate is then lost, such reduction must be very carefully used and the validity domain of the model is reduced.

In the operating domain of BSM1, most of the Monod variations are in the saturation part over the linear one. Only Monod law for S_S state variable is linear both in anoxic and aerobic phases. A line of linear regression has been estimated for each Monod law on the basis of dry, rain and storm weather files. The correlation coefficients (R) are shown in table 2.

Table 2. Linear correlation coefficient for Monod laws

	R (anoxic)	R (aerobic)
Ss	0.98	0.99
S_{NO}	0.85	0.95
$S_{ m NH}$	0.93	0.85
X_S/X_{BH}	0.97	0.97

The linear regression is validated if the correlation coefficient is greater than $\sqrt{3/2}=0.87$, which happen for laws related to S_S, S_{NH} and X_S/X_{BH} in anoxic phase, and S_S, S_{NO}, X_S/X_{BH} in aerobic phase.

However, these simplifications must be really carefully used, checking the compliance with the domain validity of the domain. As this domain may be expressed in terms of constraints on state variables, the advantage of linearizing is reduced.

3.5 Separation into aerobic and anoxic models

The separation into two models (one for anoxic phase and the other for aerobic phase) is to simplify competitive reactions by selecting those favored by the operating conditions.

The first simplification is on biomass growth reactions: due to oxygen starvation in anoxic phase, growth reactions of biomasses (ρ_1 and ρ_3) are slowed down, whereas in aerobic conditions, heterotrophic biomass growth rate (ρ_2) will be close to zero.

Combined with hydrodynamics simplification into two compartments, the simplified model shows significant deviations from the BSM1 model, particularly in the anoxic phase. Assuming that the large error on the dissolved oxygen is spreading errors on other state variables, a zero value is imposed to the dissolved oxygen concentration in anoxic phase.

Table 3 shows that the reduced model deviates the most for the readily biodegradable substrate (S_S) in both phases, nitrate and nitrite nitrogen (S_{NO}) in anoxic phase, NH_4^+ and NH_3 nitrogen (S_{NH}) in aerobic phase.

Table 3. Error due to hydrodynamic simplifications and simplified biological reactions ($S_0 = 0g_{02}$.m⁻³ anoxic)

	Anoxic pl	nase	Aerobic phase		
	Er	σ	Er	σ	
S_S (g _{COD} .m ⁻³)	39%	0.83	27.7	0.35	
X_S (g _{COD} .m ⁻³)	3.1%	2.63	8.7	5.1	
$X_{BH} \ (g_{\text{COD}}.m^{\text{-}3})$	0.3%	12	0.4%	16.1	
X_{BA} (g _{COD} .m ⁻³)	0.4%	0.65	0.5%	0.9	
S_{O} (g ₀₂ .m ⁻³)	60.4%	0.0002	117%	0.57	
S_{NO} (g _N .m ⁻³)	63.1%	0.57	15%	0.86	
$S_{\rm NH}~(g_{\rm N}.m^{-3})$	5%	0.47	51.6%	0.86	
S_{ND} (g _N .m ⁻³)	18.5%	0.17	8%	0.07	
X_{ND} (g _N .m ⁻³)	2.4%	0.14	6.5%	0.28	

In order to improve the simplified model accuracy, it is proposed to measure dissolved oxygen in aerobic phase, which is a usual and simple measurement. Results on Table 4 show that though a significant improvement for nitrate and nitrite nitrogen ($S_{\rm NO}$), some degradation occurs for other compounds.

Table 4. Error due to hydrodynamic simplifications and simplified biological reactions ($S_0 = 0g_{02}.m^3$ anoxic), S_0 aerobic measured)

	Anoxic phase		Aerobic phase	
	Er	σ	Er	σ
S_S (g _{COD} .m ⁻³)	55.2%	1.2	62.7%	0.83
X_S (g _{COD} .m ⁻³)	9.1%	9.2	16.5%	10.5
X_{BH} (g _{COD} .m ⁻³)	0.35%	12.4	0.4%	16.5
X_{BA} (g _{COD} .m ⁻³)	0.5%	0.76	0.7%	1.2
S_0 (g ₀₂ .m ⁻³)	-	-	-	-
S_{NO} (g _N .m ⁻³)	27%	0.67	15%	1.3
$S_{\rm NH}~(g_{\rm N.}m^{-3})$	23.2%	2.4	150%	4.1
S_{ND} (g _N .m ⁻³)	12.6%	0.12	8.4	0.07
$X_{ND} (g_{N.}m^{-3})$	8%	0.56	14%	0.64

As dissolved oxygen is regulated so as to insure aerobic conditions, this state variable can be eliminated from the model. The term $\mu(s_0)$ on Monod laws is then approximate to 1. This approximation is perfect for anoxic conditions

 $(S_{\rm O}{=}0)$ but in the aerobic case, this means that $S_{\rm O}$ concentration has to be significantly greater than $K_{\rm OH}{=}0.2$ to obtain a good approximation.

Table 5 highlights that nitrate and nitrite nitrogen (S_{NO}) and NH_4^+ and NH_3 nitrogen (S_{NH}) are the less adequately represented compounds. Nevertheless, other compounds are estimated with a good accuracy, and are even more precise than using dissolved oxygen measurement.

Table 5. Error due to hydrodynamic simplifications and simplified biological reactions without $S_0(\mu(S_0)=1)$

	Anoxic ph	ase	Aerobic phase	
	Er	σ	Er	σ
S_S (g _{COD} .m ⁻³)	32.4%	0.73	5.9%	0.08
X_S (g _{COD} .m ⁻³)	3.8%	5.3	5.1%	3.9
X_{BH} (g _{COD} .m ⁻³)	0.39%	13.4	0.46%	16.8
X_{BA} (g _{COD} .m ⁻³)	0.5%	0.86	0.74%	1.2
S_{NO} (g _N .m ⁻³)	210%	1.83	46.4%	3.74
$S_{\rm NH}$ (g _N .m ⁻³)	12.7%	1.74	58.7%	2.8
S_{ND} (g _N .m ⁻³)	22.2%	0.22	8.4%	0.07
X_{ND} (g _N .m ⁻³)	3.7%	0.37	4.14%	0.26

3.6 Global variables

The previous simplifications have led to a 18 state variables model. This number is much greater than the possibilities of actual measurements. However, it appears that the degradation stages (hydrolysis) of organic carbon and organic nitrogen are developed in the ASM1 model, but are not to be used for monitoring and control of the activated process. Moreover, these reactions are complex and not well known, resulting in a significant source of error.

First of all, the state variables X_S and S_S may be gathered into a single state variable, noted XS_S so that:

$$XS_S = X_S + S_S \tag{4}$$

Thus the hydrolysis reaction of the slowly biodegradable organic matter which is complex and which kinetic has three parameters would be hidden. Calculated for each of the five compartments, the Ss/XSs mean ratio is less than 3.5% even for the storm weather file, which shows that the readily biodegrable substrate (Ss) is less important than the slowly biodegrable substrate (Xs). However, the relative error is more important in anoxic tanks (37% and 25% respectively), showing an important variability of the ratio, than in aerobic tanks (8%, 6% and 6%).

These results may be interpreted by using QSSA approximation: the growth kinetics of biomasses (ρ_1 and ρ_2) corresponding to Ss assimilation are faster than carbon hydrolysis (ρ_7). Thus, Ss is assimilated by biomasses as soon as formed.

Furthermore, the state variables representing nitrogen compounds may also be gathered into one state variable:

$$S_{\rm N} = X_{\rm ND} + S_{\rm ND} + S_{\rm NH} \tag{5}$$

The concentration of nitrates and nitrites nitrogen S_{NO} can't be dismissed so as to distinguish the reactions of nitrification and denitrification. With the state variable S_N (5), the hydrolysis of organic nitrogen (ρ 8) and ammonification (ρ 6), which are very complex reactions, are hidden. On average, most present compounds are particulate organic nitrogen (X_{ND}) and ammonia nitrogen (S_{NH}) in equal share. However, the variability of these proportions is very important, causing large errors with respect to ASM1.

4. SIMULATION EXAMPLE

4.1 Model equations

Simplification assumptions are recalled:

- Hydrodynamic configuration with two perfectly mixed reactors, one anoxic and another aerobic,
- Anoxic model with biological reactions ρ_2 , ρ_4 and ρ_5 ,
- Aerobic model with biological reactions ρ_1 , ρ_3 , ρ_4 and ρ_5 ,
- Non-reactional state variables removal (S_I, X_I, X_P),
- No oxygen as state variable (S₀),
- Global state variables XS_S and $S_N(\rho_6, \rho_7, \rho_8 \text{ dismissed})$.

Fig. 3 represents the configuration of the reduced model, with the two reactors, the inputs, the outputs and the inner recycled loop. The input Z_R recycled from the clarifier is the same as for the non-reduced model.





The five state variables, noted in a Z_k vector are (k is anox or aero):

$$Z_k = [XS_S X_{BH} X_{BA} S_{NO} S_N]$$
(6)

Equations for the anoxic area are :

$$\frac{dZ_{anox}}{dt} = \frac{\left[Z_0 . Q_0 + Z_R . Q_R + Z_{aero} . Q_A - Z_{anox} . Q\right]}{V_{anox}} + r(Z_{anox}) (7)$$

$$\frac{dZ_{aero}}{dt} = \frac{\left[Z_{anox} \cdot (Q_0 + Q_R + Q_A) - Z_{aero} \cdot Q\right]}{V_{aero}} + r(Z_{aero})$$
(8)

With V_k the volume of each unit, Q represents the volume flow rates, r the vector of the observed conversion rates which are given in the tables 6 and 7. Subscripts are: 0 for biological treatment input, R for recycled loop from the clarifier, A for the inner loop from the reactor output.

4.2 Model validation

To adapt the model to the new state variables XS_S and S_N , the coefficients K_{XS} , K_N and μ_H were identified by minimizing a least-squares criterion (Levenberg-Marquardt algorithm). Thus K_{XS} is about 50 times K_S , K_N ten times K_{NH} and μ_H remains approximately at the same value. The model is validated on the storm data file (Fig. 4), which has not been used for parameter identification.

Table 6. Simplified biological model in anoxic phase

Reaction	XSs	\mathbf{X}_{BH}	\mathbf{X}_{BA}	S _{NO}	\mathbf{S}_{N}	Kinetic
$\begin{array}{c} \rho_2 \\ (X_{\rm BH} growth) \end{array}$	$-\frac{1}{Y_{H}}$	1		$-\left(\frac{1-Y_{H}}{2,86.Y_{H}}\right)$	-i _{XB}	$\mu_{\rm H} \cdot \frac{\rm XS_s}{\rm K_{XS} + \rm XS_s}$ $\cdot \frac{\rm S_{NO}}{\rm K_{NO} + \rm S_{NO}} \cdot \rm X_{BH}$
$\rho_4\left(X_{BH} \text{decay}\right)$	$1-f_P$	-1				b _H .X _{BH}
$\rho_5\left(X_{\text{BA}}\text{decay}\right)$	$1-f_P$		-1			b _A .X _{BA}

Table 7. Simplified biological model in aerobic phase

Reaction	XS_S	\mathbf{X}_{BH}	\mathbf{X}_{BA}	\mathbf{S}_{NO}	S_N	Kinetic
ρ_1 (X _{BH} growth)	$-\frac{1}{Y_{H}}$	1			-i _{XB}	$\mu_{\rm H} \cdot \frac{{\rm XS}_{\rm S}}{{\rm K}_{\rm XS} + {\rm XS}_{\rm S}} \cdot {\rm X}_{\rm BH}$
$ ho_3$ (X _{BA} growth)			1	$\frac{1}{Y_{A}}$	$-\left(\frac{i_{XB}}{+\frac{1}{Y_{A}}}\right)$	$\left(\mu_{\rm A} \cdot \frac{{\rm S}_{\rm N}}{{\rm K}_{\rm N} + {\rm S}_{\rm N}} \cdot {\rm X}_{\rm BA} \right)$
$\rho_4 \left(X_{\text{BH}} \text{decay} \right)$	$1-f_P$	-1				b _H .X _{BH}
$\rho_5\left(X_{\text{BA}}\text{decay}\right)$	$1-f_P$		-1			b _A .X _{BA}



Fig.4. Validation of the simplified model with storm data

The behavior of the state variables is very close to the reference model, even during the period of disruption due to storm event between the 4th and 5th day. The shape as well as the amplitude of the curves is very well preserved. However, the curve of $S_{\rm NO}$ is not satisfactory, due to the approximation on dissolved oxygen.

These observations are enhanced by information provided by the standard errors of each state variable (Table 8). State variables X_{BH} and X_{BA} well as XS_S and S_N state have little difference with the reference model. It is clearly visible that the average relative error of S_{NO} is important in the anoxic and aerobic zones. This error seems to be due to poor modeling of the dynamics of this variable and can be the result of the concatenation of S_N . The average differences in each of the state variables are however reasonable.

	Anoxic pha	ise	Aerobic phase		
	E_r σ		Er	σ	
XS_S (g _{COD} .m ⁻³)	15%	14	18.4%	12	
X_{BH} (g _{COD} .m ⁻³)	0.46%	13	0.46%	17.5	
X_{BA} (g _{COD} .m ⁻³)	0.8%	1.3	1.3%	2	
S_{NO} (g _N .m ⁻³)	70%	2.3	36%	4.4	
S_{N} (g _N .m ⁻³)	12%	2	20%	2.2	

Finally, this simplification can be used to predict the evolution of the global nitrogen (S_N) or carbon pollution (XS_S) , and the evolution of biomasses. It can't be use however to predict the nitrate-nitrite (S_{NO}) .

5. CONCLUSION

The objective was to study the consequences of model simplification on dynamical representativeness of the ASM1 model simulated in BSM1 conditions. Each simplification has been carefully considered. Compounds biologically inert are needed for model validation and COD measurement interpretation. Their accuracy is linked with hydrodynamic modeling and clarifier model. Hydrodynamic phenomena simplification may induce important losses of dynamical precision, especially for compounds that may usually be used for control and monitoring purposes (S_{NO} , S_{NH} , S_{O}). Nitrogen compounds and their related biological reactions are much more difficult to simplify than carbon compounds. Unexpectedly, the accuracy of the simplified model is better if the dissolved oxygen concentration is removed from the state variables and the kinetic expressions. Finally, each simplification should be chosen keeping in mind the influence of the reduction, and checking the compliance with the purpose. Nevertheless, the question to obtain a relevant simplified model remains open, and exploration of hydrodynamics phenomena and models of clarifier would enable to build new models actually representative of the dynamical accuracy of the activated sludge treatment plants and are the actual challenges.

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