Modelling of a carbon removal biological aerated filter doing partial nitrification during large-scale secondary treatment
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ABSTRACT
A wastewater biofiltration model is used to assess the potential of modelling plant-sized secondary carbon removal biofilter units. Two distinct datasets collected at the Seine-Centre biofiltration plant (Colombes, France) are used. The model is first calibrated on multiple grab samples taken at different heights inside the filter media. Data from 24 hour composite samples at the unit influent and effluent over a 2 year period are then simulated. Additional data are used to estimate hourly concentration profiles from composite samples in order to correctly use both composite and grab samples during modelling. The calibrated model is in most cases able to correctly predict the general nutrient behaviour for both datasets. The results of statistical scores such as the mean error and the mean absolute error are low for soluble components and remain correct for particles during years 2008–2009. Only one parameter set containing few heavily modified values is used to obtain these results. Modelling plant-sized biofilters appears to be practical and can be useful for easily evaluating plant optimization scenarios.

Key words | biofiltration, carbon removal, modelling, wastewater treatment

INTRODUCTION
In Europe, the Water Framework Directive requires member states to reduce carbon, nitrogen and phosphorus levels in surface water by 2015. The surface water status is defined by comparing actual pollutants levels to reference points, which account for dissolved organic carbon and ammonia, among others (France 2010). To reach these reference levels, carbon and ammonia emissions from wastewater treatment plants (WWTPs) must be tightly controlled and reduced to a minimum. The removal of pollutants in WWTPs can be performed with the help of several different technologies: activated sludge tanks, moving bed bioreactors, biofilters, etc. Biofiltration is a process that is widely used in Europe and in particular in France. During treatment, the wastewater is passed through a fixed bed of media which acts both as a filter and as a support for the growth of nutrient consuming bacteria. Under the right conditions, this process is able to reach high removal efficiencies for secondary (Canler & Perret 1994) as well as for tertiary treatment (Licskò et al. 2004).

Biofiltration is, however, not without flaws. The process’s short HRT (hydraulic residence time) requires a tight control in order to maintain an effluent quality as constant as possible. Additionally, biofilters are known to progressively clog during treatment as the filtered particles accumulate and the biofilm grows on the media. This clogging reduces the filtration and pollutant removal efficiencies. They thus need to be frequently stopped and backwashed in order to remove excess biomass. Clogging management is generally considered as a critical factor of biofiltration, especially during cold period and/or when high nutrient and particle loads are applied (Rocher et al. 2008).

The aim of this research is to assess the potential of modelling WWTPs using biofiltration for operation and control.
assistance. Previous efforts have shown that working models can indeed be used to rapidly estimate the efficiency of different plant operation scenarios (Guerrero et al. 2011). Although these estimates cannot replace empirical results from pilot experiments, they can be used to perform a relatively fast prior screening to identify the most promising scenarios to investigate. Several different models have been used in the past to reproduce the biodegradation results of diverse datasets (Le Tallec et al. 1995; Viotti et al. 2002). More recently, Vigne et al. (2010) have demonstrated the possibility of modelling the nitrification occurring in a pilot-sized biofilter. Few of these attempts have however used datasets that were both extensive and coming from full-sized plants. The work of Samie et al. (2010) has shown that it is possible to model the global chemical oxygen demand (COD) and to a lesser extent nitrogen consumption across a full biofiltration WWTP. Nevertheless, results concerning the simulation of individual biofiltration steps or other wastewater parameters remain hard to find in the literature.

The objective of this paper is to describe the calibration of a biofiltration mathematical model on several wastewater parameters from an extensive dataset coming from the carbon removal stage of the Seine-Centre WWTP (240,000 m$^3$/d, 800,000 equivalent-inhabitants), located near Paris, France. A global methodology similar to the one suggested by the IWA Good Modelling Practice task group (Rieger et al. 2012) is followed. Existing models describing each process occurring during biofiltration are first adapted and then used to reproduce effluent measurements taken under two different sampling campaigns. The model is calibrated on a short-term campaign containing several pollutants profiles inside one of the plant’s biofilters. Its performance is then compared to a long-term dataset coming from the daily monitoring of the plant.

**METHODS**

**Description of the studied WWTP**

All the data used were obtained at the Seine-Centre plant (France), which is described by the layout displayed in Figure 1. The plant is designed to receive under normal conditions 240,000 m$^3$/d. The pretreatment stage includes screening and grit/oil removal. The primary treatment then consists of nine lamellar settling tanks, which trap a large amount of suspended solids and phosphorus. Iron chloride and an anionic polymer are added as coagulant and flocculent reagents. The secondary and tertiary biological treatment are performed over three stages of biofilters: 24 Biofor® filters for carbon removal; 29 Biostyr® filters for nitrification and 12 Biofor® filters for post-denitrification using methanol as an external carbon source. Under dry conditions, the effluent flow path is linear. Under wet weather, post-denitrification is stopped as the third stage is merged with the first to maintain carbon removal under higher plant inflows. This work primarily focused on the carbon removal stage of the plant under dry conditions. Additional details concerning the complete plant operation can be found in Rocher et al. (2012a, b).

Each of the 24 Biofor® filters of the first stage has an area of 104 m$^2$ and a media bed height of 2.9 m. The Biolite media is made from expanded clay particles around 3 mm in diameter. The filters in this stage are fed wastewater and air from the bottom, in an upflow configuration. The average
hydraulic velocity and aeration loads are 4.5 ± 0.5 m/h and 1.5 ± 0.2 Nm³/m³ water. The average total suspended solids (TSS) concentration is 35 ± 11 mg/L, while total and filtered COD are 164 ± 33 and 111 ± 22 mgO₂/L, respectively, for years 2008–2011. The influent carbon loads are low enough to allow nitrification to begin in the first biofiltration stage.

Data collection and reconciliation

Ten concentration profiles over the height of the reactor (COD, TSS, NH₄⁺, PO₄³⁻) were sampled inside a single filter over a period of 2 months in the spring of 2009. The sampling consisted of grab samples at the influent as well as at six different heights in the media bed, from 0.5 to 3 m. The sampling was performed with a stainless steel cane immersed in the media bed. This cane has perforations linked to plastic tubing to extract liquid samples at desired heights. All samples were taken during dry weather daytime between 10:00 and 16:00. They were kept at 4 °C and sent the next morning to the SIAAP certified laboratory for analysis, following AFNOR standards (NF T90–101 for COD; NF EN 872 for TSS; NF EN ISO 11732 for NH₄⁺; NF EN ISO 13395 for NO₃⁻ and NO₂⁻; NF EN 15681-2 for PO₄³⁻ and NF EN 25663 for total Kjeldahl nitrogen, TKN).

The Seine-Centre plant is monitored on a daily basis for regulatory purposes. Automatic refrigerated samplers are located upstream and downstream of the carbon removal stage. The 24 hours composite samples are analysed for several parameters: COD, filtered COD, NH₄⁺, NO₃⁻, NO₂⁻, TKN, PO₄³⁻ and alkalinity. Operating conditions such as average daily water flows and hourly headloss are also measured. For the purposes of this work, dry weather data from January 2008 to September 2009 (600 days, 521 of dry weather) were used. All measurements except filtered COD were normally performed daily, with a varying amount of missing data (350–461 samples available). Filtered COD was measured infrequently during the first 432 days (254–255 samples).

An additional sampling campaign was also performed on the carbon removal stage to determine the hourly variations in carbon concentrations at the influent. An automatic refrigerated sampler was used to take grab samples every 2 hours over a 24 hour period, on 4 different days (dry weather). These samples were analysed for TSS and COD.

Before being used for model calibration, the available data first need to be processed. In order to raise the accuracy of the model’s influent inputs for the daily monitoring of the plant, a relative hourly carbon and nitrogen profile was estimated. To estimate hourly influent values during the 2008–2009 period, the 24-hour composite samples were simply multiplied by the relative profile values. For carbon, the data coming from the additional COD and TSS campaign were used to build correlations with turbidity values which were available hourly for a much longer period of time. Turbidity values over a 1 month period were transformed into COD and TSS values, which were themselves used to build the hourly profiles. In the case of TKN and NH₄⁺, data coming from NO₃⁻ sensors located after the nitrification stage over a 2 month period were used. The daily plant monitoring shows that at this stage of the treatment, most if not all of the ammonia has been oxidized. Hourly variations at this point are thus mainly caused by variations in ammonia at the influent. Data from flowmeters on three different filters were used for water flow rates. No hourly values were available for phosphorus or alkalinity and so a constant daily value had to be used for the influent.

Plant model set-up

A biofiltration model was built in Matlab® with the Simulink® toolbox, using submodels already available in the literature. The biofilter hydraulics is simply modelled as a series of six CSTRs (continuously stirred-tank reactors) of equal volume to obtain reactor hydraulics close to a plug-flow reactor while retaining reasonable simulation times (Vigne et al. 2007, 2010). Brief simulation tests indicated that simulation results did not vary much when either five, six or seven CSTRs were considered. The presence of media reduces the volume available for liquid flow by a bed porosity factor e. To simplify the model, no biological reactions occur in the liquid tanks as biomass concentrations are expected to be relatively low compared to those met in the biofilm. The biofilm model (adapted from Spengel & Dzombak 1992) divides the biofilm in several CSTRs through which soluble substrates are able to diffuse. This division is used to model the concentration gradients usually present in thick biofilms (Zhang et al. 1995). Soluble substrates are brought to and into the biofilm through
diffusion, while particular components are exchanged between liquid and biofilm surface through filtration (Horner et al. 1986; Ives 1970) and first-order detachment. Backwash efficiency is simply modelled as a removal of a fixed proportion of biofilm thickness in each reactor, using different removal efficiencies for biomass and for other, non-biomass particles. A certain fraction of media mixing across the reactors also occurs during backwash.

Biological reactions are modelled using a modified version of ASM1 (Henze et al. 1987). The modified ASM1 includes the assimilation of phosphorus as phosphates during biomass growth, in a similar way to ammonia assimilation. Nitrification and denitrification have also been modified to consider both reactions as two-steps processes. Nitritation and nitratation are modelled in the same way as the one-step nitrification of ASM1, albeit with distinct biomass and Monod parameters values. The first two denitrification reactions of ASMN (Hiatt & Grady 2008) are used for denitrification.

Model calibration

The model was first calibrated on the biofilter concentration profiles. To filter some of the variations caused by sampling and measurement errors, the data were smoothed before use. This allowed the model to be calibrated on the average behaviour of the pollutant removal found inside the media bed. Linear regressions were used in the case of TSS, NH$_4$ and PO$_4$ while a second-order polynomial was used for COD. The average smoothed profile for each nutrient was used for the calibration of the model in order to determine model parameters valid for the biofilter’s typical performances. As only a single grab influent value was available per sampled biofiltration cycle, an estimate of the concentrations and inflow values during the rest of the day was needed. The influent concentrations were considered to vary according to the hourly profiles previously described. Hourly values were estimated from these hourly profiles and the measured influent data. The biofilter backwash frequencies were synchronized with the frequencies of one unit from the carbon removal stage during simulation.

A simulation over a 30 day period using average observed influent values and operating conditions was first performed in order to obtain steady state biofilm and liquid concentrations, which were used as initial values during calibration. Thirty days of simulation were sufficient to reach a steady state in both the liquid and biofilm phases, as observed by the presence of similar concentration patterns for all variables between subsequent operation cycles. The calibration itself consisted in a dynamic simulation over 31 days: the first 30 days were used to stabilize the model while the last day was used for comparison with the average smoothed gradients. A backwash frequency of one occurrence per day was considered for both periods. Influential model parameters on the variables of interest were previously screened by performing a global sensitivity analysis using a latin hypercube design and multiple linear regressions (Saltelli et al. 2008) in a secondary treatment scenario. Parameter changes were then made one at a time to calibrate first the TSS and COD, then the NH$_4$ and finally the PO$_4$$_3^-$, making re-adjustments in an iterative way during the process. An optimal fit on a maximum amount of measured variables was desired. Initial values were re-estimated frequently as model parameters were modified. Literature reviews from Hauduc et al. (2011) and Sin et al. (2008) were used as reference points for ASM1 and two-step nitrification default parameters values, respectively.

The model was then compared to the long-term data gathered during the plant monitoring. The calibrated parameter set was tested using dynamic simulations on that second dataset and modified as necessary while ensuring that the model performance remained correct on both simulated periods. Hourly values were estimated from daily values when possible. The model accuracy was evaluated qualitatively as well as quantitatively for the long-term dataset, using several statistical scores described by Hauduc (2010). These scores are the mean error (ME), the mean absolute error (MAE), the Nash-Sutcliffe coefficient and the coefficient of determination, $R^2$. ME and MAE are, respectively, the sum of the prediction error and the absolute sum of prediction error, divided by the number of measurements used to compute the error. A relative version of these scores is obtained by dividing the ME and MAE by the average value of measured data. In both cases, these scores represent the average error of the model for each prediction. They should as such be minimized. The Nash–Sutcliffe coefficient compares the accuracy of the model to the one from an ‘average’ model, i.e. one that is constantly predicting the output to be the value of the
average measured data. A perfect model has a Nash–Sutcliffe coefficient value of 1, while values of less than zero indicate that considering a constant average value is more accurate than the model.

In order to decrease simulation times, the behaviour of only one biofilter was simulated for both datasets. In the first case, the measurements were made at the influent and effluent of a single unit, directly corresponding with the simulation set-up. In the second case, however, measurements were made at the influent and effluent of the whole secondary treatment stage and had to be adapted to fit in a one-filter set-up. The water flow rates were considered to be similar across all biofiltration units: a global value divided by the number of active biofilters was thus considered during simulation. Likewise, every filter was considered to perform the same level of treatment, implying that simulating one unit was representative of the whole plant.

Simulation times were of approximately 10–15 min for each simulation of the biofilter scale results, and around 3 hours for the 2008–2009 dataset. All simulations were run on a personal laptop computer.

RESULTS AND DISCUSSION

Hourly dynamic of the influent quality

The average hourly profiles for TSS, COD and nitrogen are summarized in Figure 2. The plant’s inflow is supplied by pumping and is nearly constant over the day, hence results are not included in Figure 2. The coefficient of determination for turbidity correlations is 0.70 for COD, but it is substantially lower for TSS, at 0.44. In all cases, a drop in concentration is observed from hours 10 to 15, followed by a peak. This peak lasts only a few hours in the case of nitrogen, while it is present almost until the end of the day for COD and TSS. The variation amplitude is smaller for nitrogen than for TSS and COD. A similar behaviour in the sewer catchment feeding the Seine-Centre plant (Clichy Aval) was observed by Mounira (2006), who attributed the difference between nitrogen and carbon profiles to a particle deposition/resuspension effect in the sewer system caused by flow variations.

As previously stated, the concentration profiles samples were all collected from 10 to 16 h which corresponds to a drop in carbon and nitrogen loadings. The average measured hourly concentration profiles thus show that the samples describe the biofilter behaviour only when its influent loads are at their lowest. Calibrating a model only on such a dataset is bound to determine a set of parameters that is only valid for a specific behaviour instead of the whole duration of a filtration cycle. The specificity of the observed behaviour will be less important for influents that do not vary importantly over the course of a day.

Calibrated parameter set

The calibrated model parameter set, as well as default reference values are presented in Table 1. Each parameter symbol is presented following the work of Corominas et al. (2010), where possible. Other parameters were left at default values. These default values were taken from Hiatt...
& Grady (2008) for the anoxic heterotrophic growth, from Sin et al. (2008) for autotrophic growth and from Henze et al. (1987) for the remaining ASM1 parameters. The physical and diffusional parameters default values were taken from the BAF model available from the GPS-X™ software (Hydromantis), which is based on the same sub-models as the model used in this study.

The backwash biofilm removal and the media packing factor were set to obtain a very rough fit on some headloss and few backwash water TSS samples that were available (not shown). Likewise, the heterotrophic anoxic yield was further decreased to obtain a rough fit on NO₃ predictions (not shown). The filter coefficient and COD to volatile suspended solids (VSS) ratio were used to calibrate the TSS removal in the media as well as its effect on COD removal. To increase global reaction rates, the diffusion resistance into the biofilm was lowered and the dissolved oxygen (DO) diffusion was increased. Ammonia oxidizers parameters were changed to adjust the ammonia predictions.

The particles’ nitrogen fractions and the ammonification rate were modified to lower the predicted TKN/NH₄⁺ ratio at the effluent, while the phosphorus fractions were used to calibrate the PO₄³⁻ removal. The fraction of media mixing during backwash was chosen to improve the fit on ammonia removal inside the biofilter, by spreading the nitrifying population across the bed height.

Few parameters related to biofilm thickness were modified during calibration. The carbon and TSS loads applied to the carbon removal biofilters at Seine-Centre are below average when compared to full-size plants observations from Canler & Perret (1994). As such, simulated biofilm thicknesses remain relatively small and almost never reach the thickness limit imposed to the model (set at 0.17 mm by the default parameter set). This maximum biofilm thickness thus rarely constitutes a limitation to the growth of bacteria in the present case. As confirmed by the sensitivity analysis results (not shown), it has a negligible influence on most simulated variables. The only major influence it has is on

<table>
<thead>
<tr>
<th>Parameter (unit)</th>
<th>Symbol</th>
<th>Default</th>
<th>Used</th>
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</thead>
<tbody>
<tr>
<td>Backwash biofilm removal fraction, biomass (-)</td>
<td>f_{XBio_back}</td>
<td>–</td>
<td>0.21</td>
</tr>
<tr>
<td>Backwash biofilm removal fraction, non-biomass (-)</td>
<td>f_{XNonBio_back}</td>
<td>–</td>
<td>0.21</td>
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<tr>
<td>Media packing factor (-)</td>
<td>β</td>
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<tr>
<td>Clean media filter coefficient (-)</td>
<td>λ₀</td>
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<td>Fraction of media mixing during backwash (-)</td>
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<td>Particular COD/VSS ratio (gCOD/gVSS)</td>
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<td>1.65</td>
</tr>
<tr>
<td>DO diffusion coefficient (m²/d)</td>
<td>D_{O2}</td>
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<td>2.85×10⁻⁵</td>
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<tr>
<td>Attached liquid film thickness (m)</td>
<td>δ_{L}</td>
<td>5×10⁻⁵</td>
<td>4.2×10⁻⁵</td>
</tr>
<tr>
<td>Heterotrophic biomass anoxic yield efficiency (-)</td>
<td>η_{YHO,Ax}</td>
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<tr>
<td>Ammonia oxidizers maximum specific growth rate (d⁻¹)</td>
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<td>1</td>
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<tr>
<td>O₂ half-saturation constant for ammonia oxidizers (gO₂/m³)</td>
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<tr>
<td>Ammonia oxidizers yield (gCOD/gN)</td>
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<tr>
<td>Ammonia oxidizers specific decay rate (d⁻¹)</td>
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<tr>
<td>Inert particles phosphorus fraction (gP/gCOD)</td>
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<td>0.005</td>
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</table>
the filtration of TSS, as it is directly involved in the equations used for computing the changes in filtration efficiency in a partially clogged filter (Ives 1970). In this case, filtration is calibrated by directly modifying the clean, maximum filter coefficient. Changes to the biofilm thickness parameters are thus not required to fit the present dataset.

Most calibrated parameters values are close to the default reference values. Nitrification-related parameters are contained in the ranges proposed by Sin et al. (2008). Other ASM1 parameters are also contained in the ranges found by Hauduc et al. (2011), apart from the temperature effect factor and the nitrogen fractions of particles, which are slightly below the ranges. The phosphorus fractions of particles are, however, much lower than the default values. The model correctly predicts the trends observed in phosphates removal with values of 0.021 gP/gCOD, but with a constant negative bias. It was thus necessary to lower the phosphorus fractions by such amplitude. The modified parameter set contains only few heavily modified values and can be considered a reasonable one. All simulation results presented in this paper used this calibrated parameter set (Table 1).

**Biofilter scale results**

Examples of the concentration profiles smoothing results are shown in Figure 3, while simulation results on the average smoothed concentration profiles are shown in Figure 4. Linear regressions are used for smoothing in the case of TSS, NH$_4^+$ and PO$_4^{3-}$. This regression method has a varying degree of success: overall TSS and NH$_4^+$ removal are well represented, but PO$_4^{3-}$ consumption shows no clear trend across the measured profiles. A linear regression is used in this case only to model the global reduction from influent to effluent. The suspended solids concentrations are on average reduced by 22 ± 8 mg/L, while phosphate reduction is of

![Figure 3](https://iwaponline.com/wqrj/article-pdf/49/3/245/379400/245.pdf)
0.33 ± 0.15 mgP/L. Nitrification is also initiated, resulting in a removal of 2.2 ± 1.8 mgN-NH₄⁺/L. A second-order polynomial is used for COD regression, to model the decrease in the removal rate observed near the last stages of the media bed. This decrease is assumed to be caused by a nearly depleted source of biodegradable carbon at the effluent. The average COD reduction is 76 ± 25 mgO₂/L.

As can be seen in Figure 4, once calibrated, the model is able to fit the average smoothed profiles quite well in the case of COD and TSS. The error bars on this figure correspond to the normalized standard deviation, i.e. the standard deviation computed after subtracting the influent value from each measurement of each profile. Although the standard deviation can be high for COD and TSS, the simulation results are very close to the average smoothed data. Calibration results are, however, not as satisfying for ammonia and phosphates. In the case of NH₄⁺, simulation results are constant over the first meter of media. The heterotrophic bacteria are known to outcompete autotrophic nitrifiers for oxygen when biodegradable carbon is available in high quantities. Nitrification should thus not be a major source of ammonia consumption in the lower parts of the media bed, where carbon levels are at their highest. NH₄⁺ then decreases in the second half of the media bed as heterotrophic competition lowers and nitrification is allowed to take place.

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This specific behaviour has been observed by others (FDZ-Polanco et al. 2000), but is not clearly present in the data measured on the Seine-Centre plant. A few of the ten available profiles exhibit similar trends, yet most show a very linear decrease in ammonia throughout the media bed. Considering the average concentration in the filter and its standard deviation however, the model’s inaccuracies remain relatively low and the global reduction is
satisfyingly simulated. The partial media mixing occurring during backwash in the model allows the simulation results to somewhat stick closer to the average smoothed ammonia profile than when mixing is not considered. It does not, however, make it fit completely, no matter the amount of mixing used.

The average smoothed phosphates profile is poorly modelled. The calibrated model predicts an initial decrease in PO$_3^-$ concentrations due to an important assimilation by heterotrophic bacteria. The assimilation then decreases as heterotrophic growth slows down and does not noticeably increase when autotrophic growth intensifies. This behaviour is in agreement with the observed COD reductions, which mostly occur before the last parts of the media bed. It is also in agreement with the observed ammonia reductions which are relatively low compared to COD. However, the average smoothed profile indicates that the phosphates consumption is constant over the media bed. This divergence is caused in part by the lack of a clearly observed trend on the PO$_3^-$ consumption. Although the normalized standard deviations are not noticeably more important for PO$_3^-$ than for other measured pollutants, in this case phosphate concentrations sometimes either rose or fell abruptly during treatment inside the media. For this reason, the calibration of phosphates consumption was performed only on the long-term plant monitoring data, as the concentration profiles were not deemed reliable enough to this end. Nevertheless, the predictions still remain inside the error bars for the most point in Figure 4.

Carbon stage scale results

The simulation results on the long-term dataset (2008–2009) are presented in Figures 5 and 6, while the statistical scores...
results are summarized in Table 2. Model update frequencies varied and occurred at a median and maximum value of 1 and 29 min, respectively. The average prediction over a complete day is used for comparison with the measured time series.

The COD predictions are on average correct, but exceptionally high or low values are not accurately predicted. The model has a tendency to ‘crunch’ the variations observed at the effluent. This is further evidenced by the important difference between the ME and MAE scores. The global bias of the model is low (relative ME of −6.9% of the average observation) yet the absolute error is much larger (21.4%). Similar model behaviour is observed for TSS with relative ME and MAE of −8.0 and 26.8%. Prediction errors on COD and TSS very often occur both at the same time. This, however, leads to different error amplitudes for each variable, as the COD to TSS ratio simulated at the effluent is different than the observed ratio. These errors are possibly caused by variations of the influent COD and TSS characteristics (i.e. when a peak in TSS is not accompanied by a rise in COD). Such variations can hardly be properly depicted by assuming a constant average COD and TSS fractionation.

Some filtered COD data (not shown in Figure 5) were available for the first 432 days of the simulation. The ME and MAE results are in this case better than for total COD. This hints that the total COD predictions weaknesses are caused in great part by particles removal. Filtration is indeed a difficult process to model, as existing deep-bed filtration models are usually built for monodispersed solutions with constant properties. Wastewater can contain several types of particles, each with their own physical and physico-chemical properties. The particles distribution can also vary in time. All these factors make the use of a single value for the filtration coefficient impractical.
Fractionating the influent TSS to consider several different removal efficiencies instead of a single average efficiency could improve the TSS removal predictions. This fractionation could be done either by using particle size distributions (Mackie & Zhao 1999) or by considering different classes of particles according to their ease of removal (Maruéjouls et al. 2012).

An additional specific dataset would, however, be required to calibrate a model using several particle classes. Such a fractionation would also be difficult to perform on a daily basis to feed the model. For these reasons, a filtration coefficient representing the average filtration efficiency thus has to be used for now. The Nash–Sutcliffe numbers for TSS and total COD are either low or near zero. This implies that the model has problems detecting and predicting positive and negative peaks, which confirms that simulation results have a tendency to remain too close to the average observed value. In the case of filtered COD, the Nash–Sutcliffe coefficient is negative. Because the measurements at the effluent are very stable in time for filtered COD, the average model remains close to observations most of the time. Each prediction error from the biofilter model thus penalizes the Nash–Sutcliffe score heavily.

The model predictions for ammonia fit the measurements over the whole range of observed concentrations. The seasonal variations observed around days 200 and 575 are also well predicted. There is however an initial period during which ammonia concentrations are slightly underestimated by the model. These inaccuracies still remain quite low: the relative ME and MAE are of –2.5 and 7.9%, respectively, while the Nash–Sutcliffe number is slightly under 0.7. The model predictions for TKN (not shown in Figure 6) follow the same behaviour with a relative ME and MAE of –5.0 and 6.5%, and a Nash–Sutcliffe number of 0.786. This implies that the global model bias on both variables is low, and that the observed ammonia and nitrogen variations at the effluent are most often correctly simulated.

Phosphates predictions also fit the observed data well, except for a small period around days 150–200. The relative ME and MAE are high at –8.4 and 22.7%, but these values are inflated by the very low average observed phosphate concentration at the filter effluent. Absolute ME and MAE are only at –0.03 and 0.09 mgP/L while the Nash–Sutcliffe number is at 0.498. Once again this implies that the model has a low bias and that it usually follows the observed variations. The Nash–Sutcliffe score is however slightly lower for $\text{PO}_4^{3-}$ than for nitrogen variables, due in part to the model underestimating the effluent concentrations during days 150–200 in this case.

Also shown for comparison sake in Table 2 are the statistical scores of the simulation results for all variables obtained when using the default parameter set (identified with the subscript ‘Def’). As only ranges of values could be found for nitrification related parameters (Sin et al. 2008),

<table>
<thead>
<tr>
<th></th>
<th>Data Number</th>
<th>ME</th>
<th>ME (%)</th>
<th>MAE</th>
<th>MAE (%)</th>
<th>Nash</th>
</tr>
</thead>
<tbody>
<tr>
<td>COD</td>
<td>458</td>
<td>–4.40</td>
<td>–6.89</td>
<td>13.66</td>
<td>21.39</td>
<td>0.199</td>
</tr>
<tr>
<td>TSS</td>
<td>351</td>
<td>–1.41</td>
<td>–7.95</td>
<td>4.77</td>
<td>26.78</td>
<td>–0.035</td>
</tr>
<tr>
<td>sCOD</td>
<td>255</td>
<td>–0.036</td>
<td>–0.10</td>
<td>5.45</td>
<td>14.96</td>
<td>–0.373</td>
</tr>
<tr>
<td>NH$_4$</td>
<td>455</td>
<td>–0.62</td>
<td>–2.51</td>
<td>1.93</td>
<td>7.86</td>
<td>0.688</td>
</tr>
<tr>
<td>TKN</td>
<td>350</td>
<td>–0.79</td>
<td>–2.96</td>
<td>1.74</td>
<td>6.53</td>
<td>0.786</td>
</tr>
<tr>
<td>PO$_4^{3-}$</td>
<td>428</td>
<td>–0.034</td>
<td>–8.39</td>
<td>0.092</td>
<td>22.73</td>
<td>0.498</td>
</tr>
<tr>
<td>COD$_{Def}$</td>
<td>458</td>
<td>28.85</td>
<td>45.18</td>
<td>32.01</td>
<td>50.14</td>
<td>–2.625</td>
</tr>
<tr>
<td>TSS$_{Def}$</td>
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<td>–4.70</td>
<td>–26.46</td>
<td>5.85</td>
<td>32.86</td>
<td>–0.466</td>
</tr>
<tr>
<td>sCOD$_{Def}$</td>
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<td>37.44</td>
<td>102.86</td>
<td>37.57</td>
<td>103.20</td>
<td>–41.224</td>
</tr>
<tr>
<td>NH$<em>4$$</em>{Def}$</td>
<td>455</td>
<td>5.94</td>
<td>24.19</td>
<td>5.98</td>
<td>24.33</td>
<td>–0.625</td>
</tr>
<tr>
<td>TKN$_{Def}$</td>
<td>350</td>
<td>6.21</td>
<td>23.26</td>
<td>6.21</td>
<td>23.26</td>
<td>–0.999</td>
</tr>
<tr>
<td>PO$<em>4^{3-}$$</em>{Def}$</td>
<td>428</td>
<td>–0.36</td>
<td>–89.12</td>
<td>0.36</td>
<td>89.12</td>
<td>–4.207</td>
</tr>
</tbody>
</table>

Table 2 | Statistical scores results for the calibrated and uncalibrated (subscript ‘Def’) model on the carbon stage scale dataset
a value located in the middle of each range was considered in this case. With the default parameter set, phosphate consumption through biomass assimilation is much too high, and the PO$_4^{3-}$ concentration is limiting both the heterotrophic and autotrophic growths. Likewise, the diffusion of oxygen is decreased importantly comparatively to the calibrated parameter set. This leads to a very high model error on filtered and total COD, as well as a constant bias on phosphate, ammonia and TKN. The accuracy of TSS filtration is however only slightly degraded.

Although efforts were spent towards the calibration of the model on backwash removal efficiency and headloss evolution, the final simulation results (not shown) remain unsatisfactory. A combination of parameters that could fit all at once the few measurements available on biofilm backwash removal intensity, initial headloss and headloss evolution during a filtration cycle could not be found. As such, related parameters were simply left at values where the model provided results on the same scale of order as observations. As shown by Vigne et al. (2011) and Osorio & Hontoria (2006), the intensity of backwashing can have an important effect on the pollutant removal in a biofilter. Improving the backwash calibration step could thus possibly lead to improvements on the results presented in Table 2. Likewise, headloss is an important operational parameter in biofiltration.

**CONCLUSIONS**

The current work has helped to confirm the potential of modelling full-sized biofiltration units performing secondary wastewater treatment. Such models were previously validated on pilot plant experiments or short term data from full-sized plants, but they had not been tested on datasets consisting of day-to-day measurements gathered over long periods of time at a large scale biofiltration WWTP. The calibrated model is in this situation able to correctly predict the general biofilter behaviour for most nutrients at different heights inside the media. It is also able to produce reliable predictions at the filter effluent over a 2 year period and is as such able to handle wide ranges of operating conditions. Both datasets were modelled using a single parameter set containing only a few parameters diverging from default and reference values. A possible improvement to the filtration equations to account for the specificities of wastewater should be investigated in order to increase the model’s accuracy on TSS and particular COD removal. Following these improvements, the model could be used both for evaluating optimization strategies and for helping the daily management of filter rotation between activity, standby and backwash states.

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