WWTP dynamic disturbance modelling – an essential module for long-term benchmarking development

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Abstract Intensive use of the benchmark simulation model No. 1 (BSM1), a protocol for objective comparison of the effectiveness of control strategies in biological nitrogen removal activated sludge plants, has also revealed a number of limitations. Preliminary definitions of the long-term benchmark simulation model No. 1 (BSM1_LT) and the benchmark simulation model No. 2 (BSM2) have been made to extend BSM1 for evaluation of process monitoring methods and plant-wide control strategies, respectively. Influent-related disturbances for BSM1_LT/BSM2 are to be generated with a model, and this paper provides a general overview of the modelling methods used. Typical influent dynamic phenomena generated with the BSM1_LT/BSM2 influent disturbance model, including diurnal, weekend, seasonal and holiday effects, as well as rainfall, are illustrated with simulation results. As a result of the work described in this paper, a proposed influent model/file has been released to the benchmark developers for evaluation purposes. Pending this evaluation, a final BSM1_LT/BSM2 influent disturbance model definition is foreseen. Preliminary simulations with dynamic influent data generated by the influent disturbance model indicate that default BSM1 activated sludge plant control strategies will need extensions for BSM1_LT/BSM2 to efficiently handle 1 year of influent dynamics.

Keywords Activated sludge; benchmark; disturbances; modelling; BSM1; BSM1_LT; BSM2

Introduction

The IWA/COST benchmark system is a protocol that allows objective comparison of the effectiveness of control strategies in biological nitrogen removal activated sludge plants. The first benchmark implementation (Copp, 2002), Benchmark Simulation Model No. 1 (BSM1), is a success. This is illustrated by the large number of scientific papers – more than 100 according to Jeppsson and Pons (2004) – using the benchmark or part of the benchmark (e.g. influent files, plant performance evaluation criteria).

The BSM1 definition consists of the model, an associated control system, a benchmarking procedure and plant performance evaluation criteria. The model is a five reactor activated sludge plant configuration with a (non-reactive) secondary clarifier, utilising the Activated Sludge Model No. 1 (ASM1) for modelling of the biological reactions (Henze *et al.*, 1987) and a 10-layer Takács model describing the clarifier (Takács *et al.*, 1991). Model parameter values and files characterising the influent wastewater are also provided. Although considerable flexibility is provided so as not to limit the creativity of the user-defined control strategy to be tested, only specified control handles and sensors are to be used. The benchmarking protocol represents a step-wise procedure that includes implementation, initialisation and evaluation of treatment plant and control system performance using a predefined 1-week evaluation period. The evaluation is carried out according to a number of specified criteria, including effluent quality, operational cost, sludge production, energy usage and number/magnitude of effluent violations.

Although a valuable tool, the intensive use of BSM1 has also revealed a number of limitations. BSM1 has, for example, been used to demonstrate the performance of process

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monitoring algorithms (e.g. Yoo *et al.*, 2002). Monitoring of wastewater treatment plant (WWTP) operation has recently become an active research area where many different methods have been proposed (Rosen *et al.*, 2003). Similar to the comparison of local WWTP control strategies before the introduction of BSM1, there is no objective way for comparing the suitability of proposed monitoring methods. Most monitoring methods, when published, are validated on a plant-specific data set that is usually not publicly available. The availability of only a limited influent data sequence (= external disturbances), and the fact that the definition of a realistic set of internal disturbances (e.g. sensor and actuator failures) is lacking, effectively means that BSM1 is not a feasible alternative for benchmarking process monitoring systems. A tentative benchmark system, Long-Term Benchmark Simulation Model No. 1 (BSM1_LT), has therefore been proposed as an extension to BSM1 to fill this gap (Rosen *et al.*, 2004), focusing on long-term process monitoring performance evaluation.

A second limitation of BSM1 is that only local control strategies can be evaluated, since the BSM1 definition only includes an activated sludge system and a secondary clarifier. During the last decade the importance of integrated, plant-wide control has been recognised. It is for example known that the sludge reject water, a byproduct of the final sludge concentration step in the sludge treatment, represents a significant nutrient load. Consequently, controlled dosing of the reject water to the activated sludge plant can result in considerable improvement of the plant performance. Accordingly, when aiming at achieving optimal system performance, the complete WWTP should be considered to avoid suboptimal solutions: primary and secondary clarification units, activated sludge reactors, anaerobic digesters, thickeners, dewatering systems, etc., are linked together in a WWTP. They need to be operated and controlled not only on a local level as individual processes, but also by supervisory systems taking into account all the interactions between the processes. Inspired by BSM1, a proposal for the plant-wide Benchmark Simulation Model No. 2 (BSM2) was recently presented (Jeppsson *et al.*, 2004), basically extending the BSM1 with a primary clarifier and sludge treatment processes.

WWTP disturbance modelling is important for BSM1_LT and BSM2, and will include modelling of external (= influent related) and internal (= process related, e.g. failure of sensors or actuators) disturbances. In this paper, we discuss aspects of the influent-related disturbance model definitions, which will form one of the essential modules for long-term benchmark development. Preliminary simulation results obtained with some of the disturbance models during the development phase are used for illustrative purposes. It should indeed be emphasised that this paper contains proposals, not a final definition, as BSM1_LT and BSM2 are still in a development phase. It is the intent that this paper will initiate further discussions within the scientific community and allow consensus to be reached on external and internal dynamic disturbance models for BSM1_LT and BSM2.

Motivation for WWTP disturbance modelling

One year evaluation period

Common to the BSM1_LT and BSM2 proposals is an extension of the monitoring system or control strategy evaluation period from 1 week to 1 year. The evaluation of control strategies in BSM1 is done based on three different 'weather files', corresponding to dry, storm and rain weather disturbance scenarios (Copp, 2002). For each of these influent disturbance scenarios 1 week of dynamic data with a 15-min sampling interval are used to evaluate the impact of a proposed control strategy on the simulated plant performance. There is a general consensus that 1 week of data is not sufficient to evaluate WWTP controller performance, especially not when 'slow' actuators such as the waste sludge flow rate are manipulated. However, even in the case of 'fast' actuators such as the oxygen supply, changes in the dissolved oxygen (DO) set point showing good system performance in the relatively short performance evaluation window provided by BSM1 might in the long term lead to problems, for example due to a slow decrease of the amount of nitrifying biomass (X_{BA}) in the system when the DO set point is maintained at an insufficient level. Such a decrease of X_{BA} would probably only affect the plant performance after one or two sludge retention times. An increase of the control strategy evaluation period from 1 week to 1 year can thus be considered the logical step towards a more realistic framework for evaluation and comparison of control strategies. Where BSM1 intrinsically allows delaying potential WWTP operational problems resulting from selecting a specific control strategy, this should no longer be possible in BSM2. In that respect, the start of the BSM1_LT/BSM2 monitoring/control strategy evaluation period is intentionally during the warmest period of the year, instead of starting (and ending) during the coldest period, to avoid that potential operational problems during the cold weather period could be 'delayed' until after the performance evaluation period.

Why model WWTP disturbances?

Practically, the BSM1_LT/BSM2 simulation models need to be initialised by simulating the model over a long period of time using a constant influent composition, aiming at reaching a steady state. In the case of BSM1_LT, for example, the flow-weighted average BSM1 influent composition at a temperature of 15 °C will be used for this purpose. Starting from the steady state, the BSM1_LT/BSM2 will subsequently be simulated using dynamic influent data with 15-min sampling interval. The BSM1_LT, for example, will first be simulated using 9 weeks of dynamic influent data to enable the system to reach a dynamic 'pseudo' steady state. Afterwards, the plant is simulated for an additional 1.5 years of dynamic influent data: the first 6 months of these dynamic data, starting on 1 January (winter period), produce data that can be used for training of monitoring strategies and/or control algorithms. The last 12 months, starting on 1 July (summer period) correspond to the monitoring/control strategy evaluation period, and is used for comparing different algorithms and strategies.

When it comes to defining an influent data set for BSM1_LT/BSM2, one could have chosen to collect data on a real system to generate an influent file similar to BSM1. However, creating suitable influent characteristics using models has been selected as the better way. Several reasons can explain why a model is preferred: (1) Due to the large amount of influent data needed for simulating BSM1_LT/BSM2, it is almost impossible to collect such a data set of consistent quality on a real system. (2) Using influent data collected on a full-scale system would most probably result in a very specific data set, where some phenomena would be very prominent, whereas others would be absent. An influent model allows the benchmark developers to generate an influent file containing all the characteristics that are considered to be necessary for a thorough evaluation of the monitoring algorithms/control systems in BSM1_LT/BSM2. (3) A model for producing dynamic influent profiles will minimise influent generation efforts since the same influent can be re-used for BSM1_LT and BSM2. With respect to influent characteristics, the main difference between BSM1_LT and BSM2 is that BSM2 includes a primary clarifier, whereas BSM1_LT does not. It will be assumed that the same influent model can be used for both BSM1_LT and BSM2, where the BSM1_LT influent corresponds to the BSM2 effluent of the primary clarifier (Figure 1). (4) Even when a suitable influent data set, including flow rates and pollutant concentrations (e.g. soluble COD (COD_{sol}), particulate COD (COD_{part}), ammonium nitrogen (S_{NH}), Kjeldahl nitrogen (TKN)), could be collected, there would still remain a modelling task. Some of the phenomena that are envisaged to be included in BSM1_LT, such as toxic influent shock loads to the plant, would

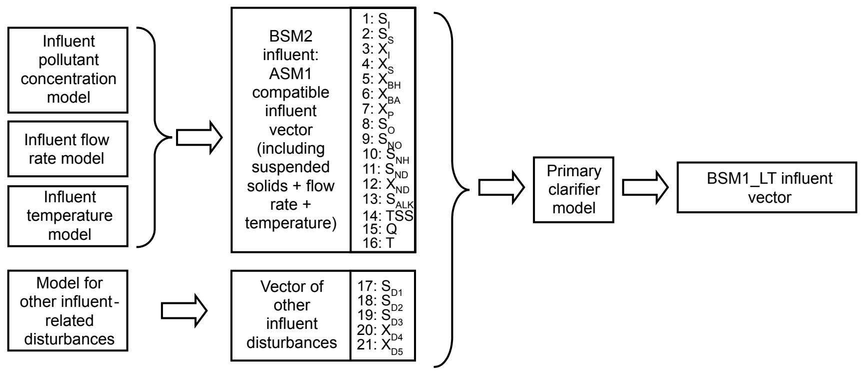

Figure 1 Schematic representation of the generation of the different parts of the BSM1_LT and BSM2 influent vectors

indeed necessitate a model to generate suitable influent toxicant dynamics, since specific chemicals are usually not monitored on-line in the treatment plant influent. (5) Producing a model to generate WWTP influent disturbance scenarios can have applications that reach far beyond the BSM1_LT/BSM2 system. The influent model can, for example, be extended easily to be compatible with the complete IWA activated sludge model family (Benedetti *et al.* 2005; Raduly *et al.*, 2005).

External WWTP disturbance modelling

This paper mainly attempts to highlight some features of the external WWTP disturbance models, and especially also the reasons for implementing some specific features. Further details on the implementation of specific submodels can be found in Gernaey *et al.* (2005).

External WWTP disturbances: model structure and influent vector

A schematic representation of the external WWTP disturbance model structure currently developed for the IWA/COST benchmark system extensions is provided in Figure 1. Four submodels will each generate a part of the influent vector. The submodels are not mechanistic (or physical), i.e. they do not contain detailed process knowledge on specific processes. The submodels should rather be termed 'phenomenological models', that is models that reproduce typical phenomena observed in the influent of full-scale WWTPs with a minimum number of parameters (see Gernaey *et al.* (2005) for further details).

Combining the contributions from the influent pollutant concentration model, the influent flow rate model and the influent temperature model gives a dynamic influent vector for BSM2 consisting of 16 states (13 ASM1 states + suspended solids + flow rate + temperature). As mentioned earlier, this dynamic influent vector will be used both for BSM2 and BSM1_LT. The effluent of the primary clarifier of the BSM2 configuration, which at this moment is modelled according to Otterpohl and Freund (1992) and Otterpohl *et al.* (1994), will therefore serve as the influent vector for BSM1_LT. To compare the impact of additional influent disturbances on the control and/or monitoring strategies using BSM1_LT, five additional influent states are available. These 'dummy states' have not been defined in detail yet, but are envisaged to be used for, among other things, modelling the occurrence of a toxic shock load or inhibiting substances in the influent. Both soluble and particulate 'dummy states' are foreseen, which will for example facilitate the distinction of a soluble toxic component on the one hand, which will be quickly diluted by the influent wastewater, and a toxic component that will adhere to the biomass on the other hand, and may stay in the system for several sludge ages.

The influent flow rate model (Figure 1) contains contributions from households, industry, rainfall and groundwater infiltration. A detail on the influent model structure, more specifically the influent pollutant concentration model structure, is provided as an example in Figure 2 to illustrate the principles of the 'phenomenological models' that form the basis for the BSM2 influent generation. The schematic representation of the influent pollutant concentration model structure should be read from left to right, since the large arrow in Figure 2 indicates the direction of the signal flow within the model.

The influent concentration profiles are generated based on a number of seed files, which for example consist of diurnal pollutant flux profiles for the wastewater derived from households. For households, the seed files are normalised (mean = 1), and are converted to units of g COD or g N per person equivalent (PE) per day by multiplication with an appropriate gain, corresponding to the average daily COD or N load per PE. This has the advantage of scalability. Multiplying these profiles with the number of PE in a catchment area will result in the total pollutant flux from households. In this case, it was assumed that the households generate 80% of the COD load to the WWTP, and 90% of the N load. The second contribution to the influent pollutant load consists of pollutant fluxes from industrial activity. These diurnal profiles are sampled in a cyclic manner and are combined with two other files that include a weekend effect and a holiday effect, respectively, both resulting in a decrease of the pollutant flux. Zero-mean white noise is added to the pollutant fluxes, and the COD and N pollutant fluxes are passed through an

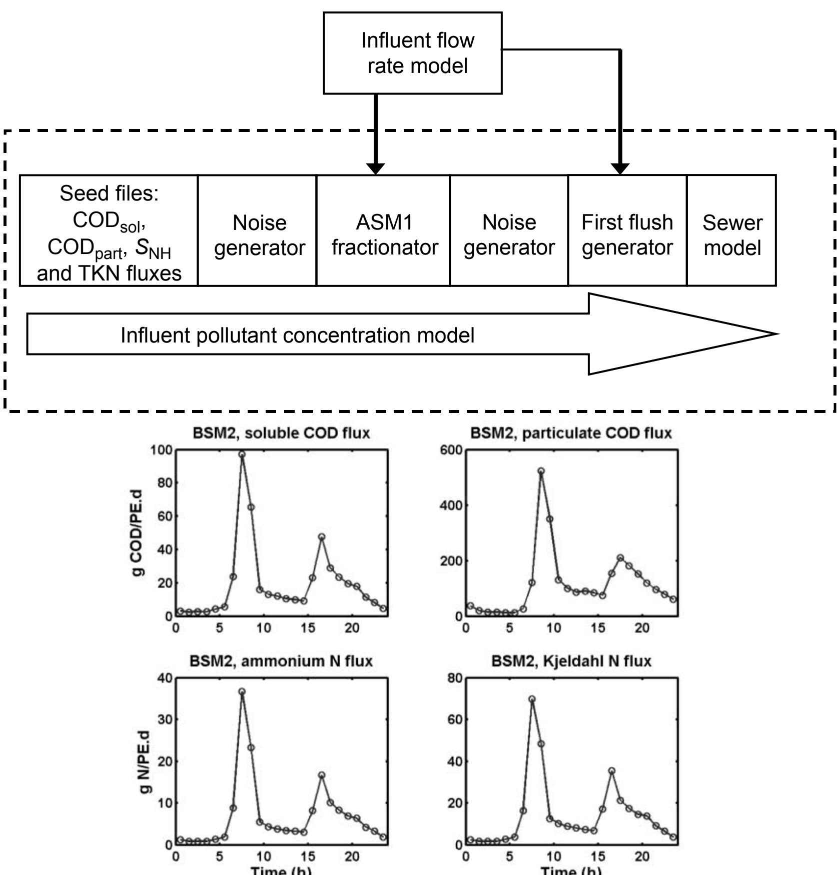

Figure 2 Left: signal flow and different sub-models in the influent pollutant concentration model; Right: seed files for the COD_{sol}, COD_{part}, S_{NH} and TKN fluxes per PE

ASM1 compatible influent fractionator. This fractionator has the wastewater flow rate as an input, such that pollutant fluxes are converted into concentrations, i.e. a vector of ASM1 states. Similarly to BSM1, it is assumed that the influent concentrations of autotrophic biomass (X_{BA}), particulate products resulting from biomass decay (X_P), oxygen (S_O) and nitrate nitrogen (S_{NO}) are equal to zero. The ratios for the fractionation of the pollutant fluxes, for example the conversion of COD_{part} into particulate inert material (X_I), slowly biodegradable substrate (X_S) and heterotrophic biomass (X_{BH}), are derived from the BSM1 flow-weighted average dry weather influent composition. The ASM1 pollutant concentration vector is then passed through a noise generator, a first-flush effect generator and a sewer model. The noise generator, again adding zero-mean white noise, is included for reducing the correlation between the influent concentration profiles, e.g. for X_I, X_S and X_{BH}. Not including this feature would mean that estimating the influent X_S concentration, e.g. assuming a respirometer as a sensor located on the influent line, would automatically imply perfect knowledge of influent X_I and X_{BH} concentrations. Due to the noise generators mass balances do not hold. The first-flush generator also has the influent flow rate as an input, to allow large rain events to trigger a first-flush effect. The sewer model consists of variable volume tanks in series, and will mainly influence the shape of the influent concentration profiles. Further details on the sewer model are provided in Gernaey *et al.* (2005).

Examples

Features of the influent model: BSM2 versus BSM1_LT

The influent model (Figure 1) includes effects on different time scales. The fastest phenomena are diurnal flow rate and concentration variations, and rain events. A holiday effect, lasting over several weeks and consisting of a reduction of the pollutant fluxes and the wastewater flow rate, is also included. The slowest effect considered in the influent model is the seasonal correction on the influent flow rate, which mimics the effect of seasonal evaporation variations: a high infiltration rate during the colder period and a low infiltration rate during the warm period. A similar seasonal variation is included for temperature, which will vary over the year according to a sine wave, with a minimum of 10 and a maximum of 20 °C.

Some influent model features are illustrated in Figure 3. The influent flow rate profiles in Figure 3a illustrate the dynamics of the dry weather and the total influent flow rate profiles. The dry weather flow rate profiles are included for illustration purposes only. Obviously, the total flow rate, corresponding to the dry weather flow rate with rain events added to it, represents the proposed BSM2 influent flow rate dynamics. The diurnal influent flow rate profiles, with two peaks each day, appear clearly in the dry weather influent flow rate data. The weekends, 2 consecutive days with a lower average flow rate that appear each week, are difficult to distinguish due to the effect of the noise generators. The largest rain events correspond to the largest peaks in the total influent flow rate profile in Figure 3(a). Three influent suspended solids (TSS) profiles are provided in Figure 3(b). The top one corresponds to the dry weather BSM2 influent profile, and is again provided for illustration purposes. The TSS profile in the middle represents the BSM2 influent TSS concentration dynamics, with a clear dilution of the influent TSS whenever a rain event occurs. The last TSS concentration profile gives an idea of the TSS concentration dynamics in the effluent of the primary clarifier, which corresponds to the influent concentration dynamics to be used for BSM1_LT. Compared to the BSM2 influent, about 50% of the TSS has been removed in the primary clarifier.

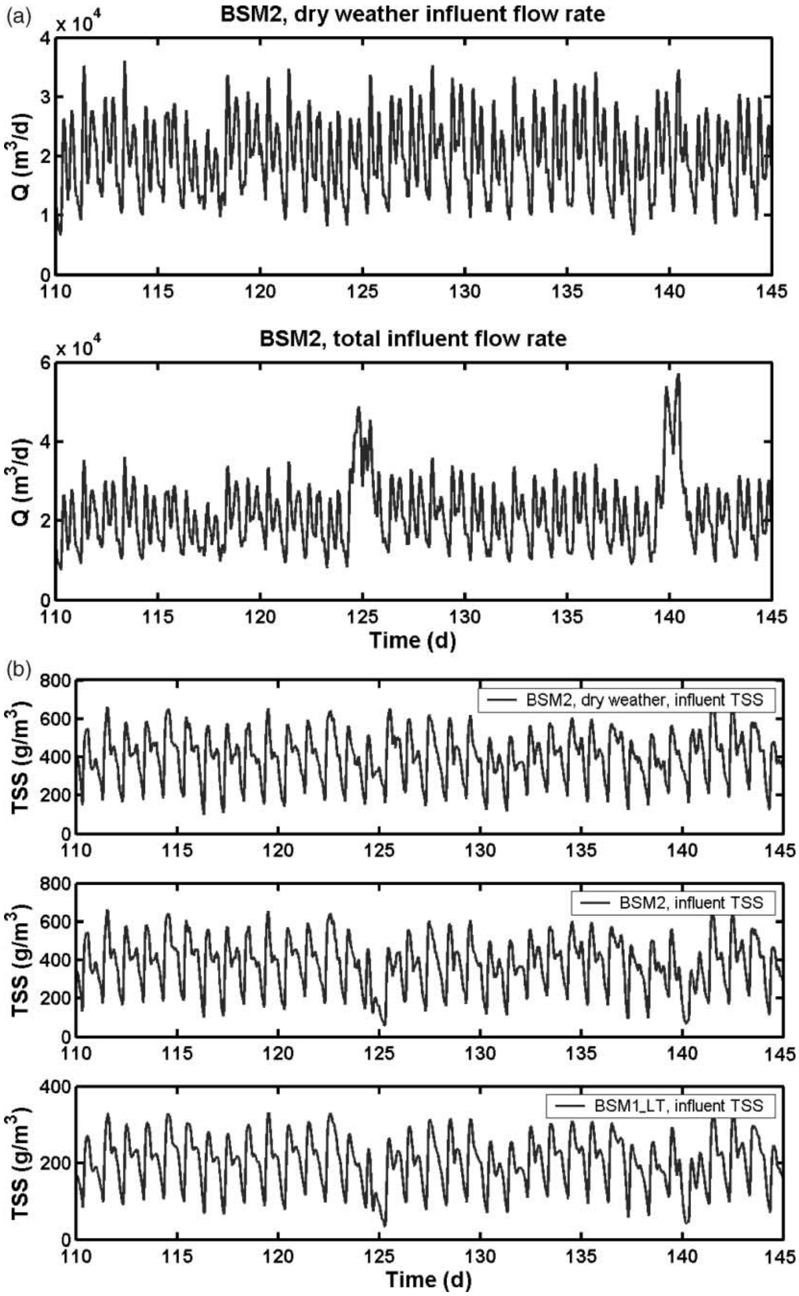

Figure 3 Model-based generation of (a) BSM2 influent flow rate dynamics; dry weather versus total (= dry weather + rainfall) influent flow rate; (b) influent suspended solids concentration dynamics for BSM2 (top: dry weather; centre: dry weather + rainfall) and BSM1_LT (bottom)

BSM1_LT: first simulation results

The BSM1_LT plant, obtained by extending the ASM1 process rates of the BSM1 with temperature dependency, was simulated to demonstrate the effects of considering dynamic influent flow rate, pollutant concentration and temperature variations on the simulated plant performance. The BSM1_LT simulation procedure was explained before. When only using the default BSM1 controllers (DO control in reactor 5, and control of the internal recirculation, see (Copp, 2002)), the simulations showed that

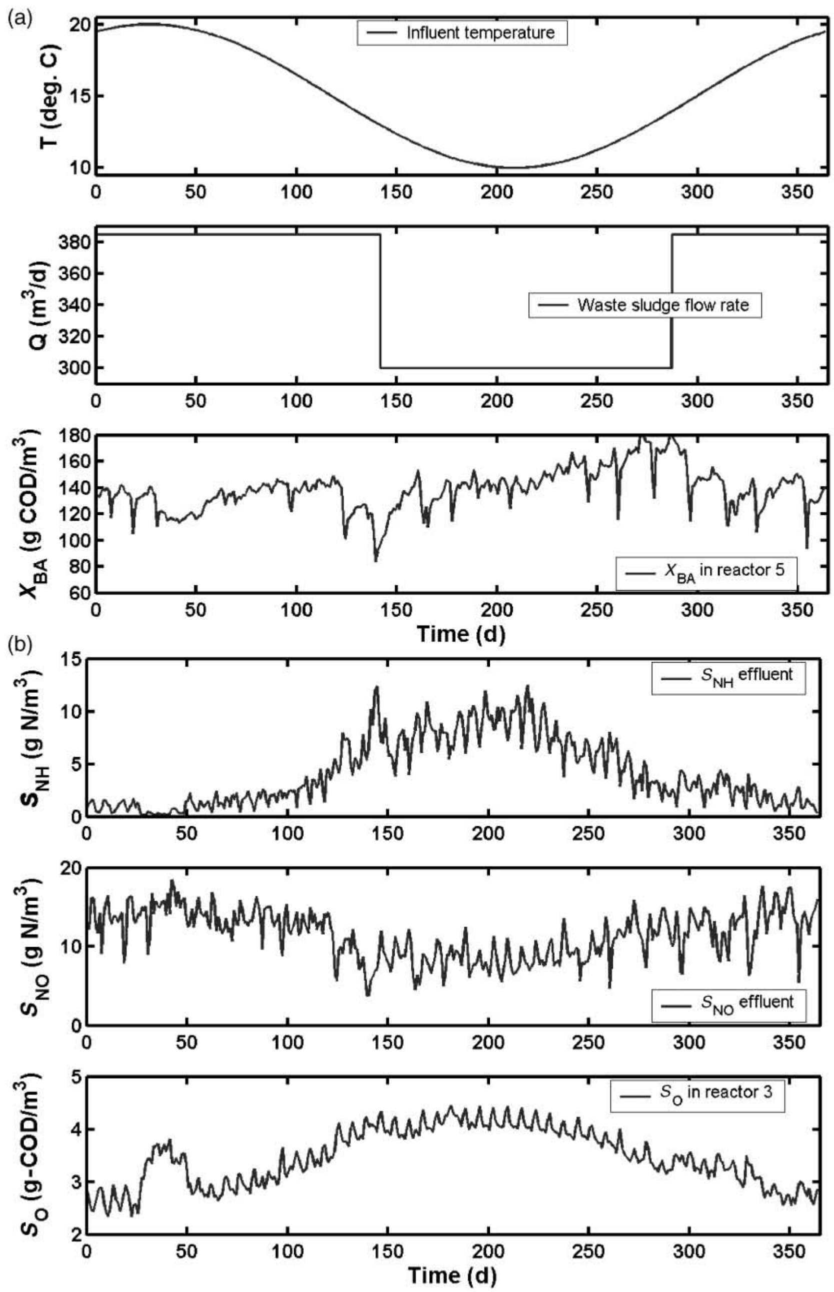

Figure 4 Simulation results obtained with the BSM1_LT influent. Time = 0 corresponds to 1 July (a). Influent temperature dynamics (daily average values: one value per day, corresponding to the average of 96 dynamic data points), waste sludge flow rate (centre), and X_{BA} concentration (daily average values) in the last aerated tank (bottom). (b) Daily average values for effluent S_{NH} (top), effluent S_{NO} (centre) and S_O concentration in the first aerobic tank (bottom)

effluent S_{NH} concentrations become very high during the coldest period of the year, reaching peak values above $30\,g\,N/m^3$. This provides a strong indication that modifications will be needed with regard to the existing default BSM1 controllers, to allow for more realistic BSM1_LT simulation results. An extension of the aerated volume and a reduction of the waste sludge flow rate are obvious control measures to increase the nitrification capacity in the system during periods with a low influent temperature. We selected the last option: to compensate partly for the temperature effects, the two default BSM1 controllers were extended with a simple waste sludge controller. The S_{NH} concentration measured in the fifth reactor was passed through a first-order filter (time constant of 10 days), and the resulting signal was used as an input to a relay that switched the waste sludge flow rate from high ($=385\,m^3/d$) to low ($=300\,m^3/d$) when the input to the relay became higher than the S_{NH} set point ($5\,g\,N/m^3$ in this example), and vice versa. Results (Figure 4) correspond to the last year of data, i.e. what is assumed to be the monitoring method evaluation period in BSM1_LT, and focus on the simulated N removal efficiency.

Figure 4a illustrates the operation of the suggested waste sludge flow rate controller. During the warm period the waste sludge flow rate equals $385\,m^3/d$. However, when the influent temperature decreases, the X_{BA} concentration in the plant also decreases, to reach a minimum around $t = 140$ d. As a consequence of the decreasing X_{BA} concentrations, combined with the reduced nitrification rates due to the low temperature, the effluent S_{NH} concentration increases (see Figure 4b, top). The waste sludge flow rate is suddenly reduced from 385 to $300\,m^3/d$ to compensate for the nitrification capacity decrease. As a consequence, the X_{BA} concentration stabilises around $130\,g\ COD/m^3$ in reactor 5. As soon as temperatures are sufficiently high again, the X_{BA} concentration increases and the effluent S_{NH} concentration decreases, such that the waste sludge flow rate is switched back to $385\,m^3/d$ at $t = 280$ d. Effluent S_{NO} concentrations are low during cold periods, and higher during warm periods due to a lack of readily biodegradable carbon for denitrification in the plant.

The specific oxygen transfer coefficient (K_La) in reactors 3 and 4 equalled $360\,d^{-1}$, whereas S_O was controlled at $2\,g\text{-}COD/m^3$ in reactor 5. Daily average S_O concentrations (Figure 4b, bottom) indeed indicate a severe effect of temperature on the process rates. During the warm period, the average S_O concentration in reactor 3 is higher than $2\,g\text{-}COD/m^3$, with dynamic variations (data not shown) ranging from 1.5 to $4\,g\text{-}COD/m^3$. During cold periods, the average S_O concentration in tank 3 reaches about $4\,mg\text{-}COD/m^3$. This also indicates that default BSM1 control strategies will need to be extended, for example with DO controllers in all aerated tanks, to realistically handle 1 year of dynamic influent data with all its typical dynamic phenomena. A default control strategy for the BSM1_LT, a reference point for future BSM1_LT users, is at this moment under development.

Conclusions and perspectives

Influent disturbance models allow creating influent dynamics for BSM1_LT and BSM2, including diurnal, weekend, seasonal and holiday effects, as well as rainfall. As part of the benchmark development, a proposed influent model/file has been released to the benchmark developers for evaluation purposes. As a result of this evaluation, a final BSM1_LT/BSM2 influent disturbance model definition is planned. Preliminary simulations with dynamic influent data indicate that default BSM1 activated sludge plant control strategies will need extensions to handle 1 year of influent dynamics.

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