Available online at www.sciencedirect.com
ScienceDirect
Environmental Modelling & Software 23 (2008) 1082–1091
Environmental Modelling & Software
www.elsevier.com/locate/envsoft

Tools to support a model-based methodology for emission/immission and benefit/cost/risk analysis of wastewater systems that considers uncertainty

Lorenzo Benedetti [a,*], Davide Bixio [b], Filip Claeys [a], Peter A. Vanrolleghem [a,c]

[a] *BIOMATH—Department of Applied Mathematics, Biometrics and Process Control, Ghent University, Coupure Links 653, 9000 Ghent, Belgium*
[b] *Technology Department, Aquafin NV, Dijkstraat 8, 2630 Aartselaar, Belgium*
[c] *Département de génie civil, modelEAU, Pavillon Pouliot, Université Laval, Québec, QC G1K 7P4, Canada*

Received 3 May 2007; received in revised form 29 December 2007; accepted 3 January 2008
Available online 15 February 2008

Abstract

This paper presents a set of tools developed to support an innovative methodology to design and upgrade wastewater treatment systems in a probabilistic way. For the first step, data reconstruction, two different tools were developed, one for situations where data are available and another one where no data are available. The second step, modelling and simulation, implied the development of a new simulation platform and of distributed computation software to deal with the simulation load generated by the third step, uncertainty analysis, with Monte Carlo simulations of the system over one year, important dynamics and stiff behaviour. For the fourth step, evaluation of alternatives, the evaluator tool processes the results of the simulations and plots the relevant information regarding the robustness of the process against input and parameters uncertainties, as well as concentration–duration curves for the risk of non-compliance with effluent and receiving water quality limits. This paper illustrates the merits of these tools to make the innovative methodology of practical interest. The design practice should move from conventional procedures suited for the relatively fixed context of emission limits, to more advanced, transparent and cost-effective procedures appropriate to cope with the flexibility and complexity introduced by integrated water management approaches.

Keywords: Wastewater treatment plant design; Cost–benefit analysis; Risk; Modelling and simulation; Software tools; Grid computing

1. Introduction

Process choice and dimensioning of wastewater treatment plants (WWTPs) is a particularly sensitive step to cost-efficiently comply with regulatory standards. This step accounts only for a small fraction of the up-front costs, but it can lead to substantial savings over the life span of a plant if done adequately.

With the new water quality based approach introduced with the European Water Framework Directive (WFD) (CEC, 2000), the design of the systems is far less predetermined and the options to meet the goals become much more numerous, due to the wider system boundaries—the integrated wastewater system includes the draining catchments, sewers, WWTPs and receiving waters—which make that the options available to the decision maker are the combinations of all options available for each of the subsystems. Therefore, new (model-based) design methodologies must be developed in order to be able to cope with such increased complexity in a cost-efficient way. Achleitner et al. (2007) developed a tool which can perform fast long-term (e.g. 20 years) simulations of the integrated wastewater system focusing on hydraulic phenomena and using very simplified models for pollution processes. Fu et al. (2008) and Vanrolleghem at al. (2005) show examples of detailed mechanistic models for real time control (RTC) of the integrated wastewater system based on receiving water quality criteria. A tool which goes in the direction of automated design (limited to WWTPs) is presented by Rivas et al. (2008).

The real-life application of models and software for integrated modelling of urban wastewater systems (WWTP, sewer

* Corresponding author. Tel.: +32 9 264 5937; fax: +32 9 264 6220.
E-mail address: lbene@biomath.ugent.be (L. Benedetti).

1364-8152/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.envsoft.2008.01.001

and river) encounters several problems due to their complexity. First of all, it is very difficult to obtain the data required to calibrate such models that contain a large number of parameters. The inputs to these models are very uncertain because of the difficulty and cost of collecting the high frequency (hourly-basis) data, the extensive periods needed to cover seasonal variability and the scattered responsibilities in collecting the data.

Another issue is the large number of equations involved, which makes simulations of integrated models very time consuming. This is further aggravated by the fact that the many different time scales of the modelled process make the model stiff, therefore slower to be integrated with most of the numerical solvers. A possibility to overcome this problem and have much faster simulations is to use ''black-box'' models like artificial neural networks (Ráduly et al., 2007), at the cost of losing the flexibility of mechanistic models with regard to modifications of the system layout and of restricting the domain within which the model is valid.

On top of that, the already heavy calculation burden is increased by several orders of magnitude when uncertainty assessment is included, as this typically requires Monte Carlo simulation.

A systematic methodology to evaluate system design/upgrade options under the above difficult conditions has been introduced in Benedetti et al. (2006a). This methodology would be of limited practical use without the support of adequate software tools. This paper illustrates the tools developed for the steps constituting this methodology. The four steps are: (1) data collection and reconstruction, (2) modelling and simulation, (3) uncertainty assessment and (4) evaluation of alternatives, based both on effluent quality (emission-based) and on receiving water quality (immission-based).

2. Tools for data collection and reconstruction

A weak point in many simulation studies is the limited availability of long time series representing realistic dynamic influent disturbance scenarios. There is a necessity to have adequate influent time series because the natural diurnal, weekly and seasonal variations and episodic events (e.g. ''first flush'' induced by rain events) represent the main process disturbance.

In the presence of some actual data, influent time series can be reconstructed, using available measurements and making assumptions on the influent properties (e.g. as in Bixio et al., 2002 and Devisscher et al., 2006). In case of the complete absence of data, a realistic influent time series can be generated by a phenomenological model of the sewer catchment driven by rain series, which is typically available for the region of concern (Gernaey et al., 2005).

A tool has been developed in Matlab/Simulink to account for these situations, as explained below.

2.1. Case with some data available

The approach taken in this case can be summarised as follows.

If sufficient daily measured flow rate values are available, they are used directly, and classified into dry and wet days. Given the scarcity of water quality data, the pollutant load is computed from seasonal averages. To these synthetic daily sequences, factors are applied to account for weekends, or for first flush events (identified by checking whether a rain event appears after a number of dry days or after a rainy day) when different empirical factors are applied for particulate and soluble compounds. A daily pattern is applied to the flow rate, and concentrations are calculated from load and flow rate. An example is shown in Fig. 1.

If daily flow rate values are not available, they are generated from a seasonal Poisson distribution, after which they undergo the same treatment as the flow rate values taken from data.

2.2. Case with no data available

A simple phenomenological model was implemented, aimed at providing realistic WWTP influent dynamics without pretending at any point to provide a basis for studying urban drainage system mechanisms in detail.

Three basic modelling principles were applied: (1) model parsimony, limiting the number of model parameters as much as possible; (2) model transparency, for example by using model parameters that still have a physical meaning; (3) model flexibility, such that the proposed influent model can for example be extended easily for other applications where long influent time series are needed.

The proposed influent model produces dynamic influent flow rate and pollutant concentration trajectories. An example of the model structure relative to flow rate is shown in Fig. 2.

Water flows are generated adopting *per capita* discharges in households and industry (with daily, weekly and seasonal profiles), by rainfall-runoff on impervious surfaces connected to the sewer and by infiltration in the sewer from the soil compartment.

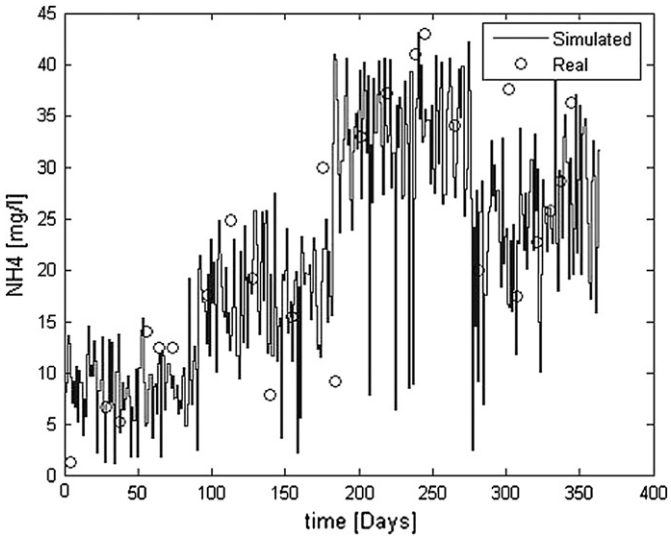

Fig. 1. Example of a synthetically generated influent series and real data. From Devisscher et al. (2006).

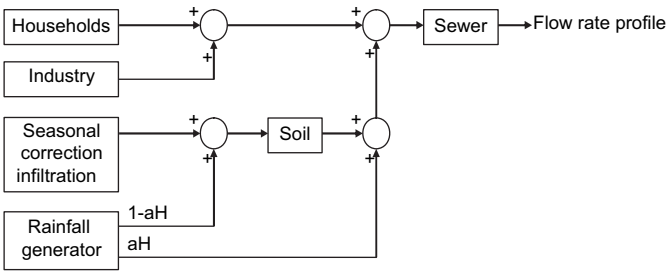

Fig. 2. Schematic representation of the influent flow rate model; *aH* is the fraction of impervious surface. From Gernaey et al. (2005).

The soil is modelled as a variable volume tank with the level being function of rainfall on pervious area and of an influent with seasonal variation representing the upstream aquifer. If the water level in the soil tank is higher than the invert level at which the sewer is placed, infiltration occurs at a rate function of such water level.

Rainfall can be either given as measured data (input file) or generated by a simple rainfall model.

The sewer is modelled as a series of tanks with variable volume describing flow propagation. The size of the sewer system can be selected, assuming that a relatively small sewer system will result in sharp diurnal concentration peaks, whereas a large sewer system will result in smooth diurnal concentration variations.

The example given in Fig. 3 shows how that effect is achieved. In the case of very small sewer networks, all the inflow passes only through the line with one block (each block consists of three tanks in series), while with a large sewer network the inflow will be evenly distributed to the four parallel lines. The model actually allows to choose to have up to eight parallel lines.

Pollutant loads are generated adopting *per capita* discharges in households and industry (with daily and weekly variations) for soluble COD, particulate COD, total nitrogen and total phosphorous. Sedimentation and re-suspension equations are included in the sewer model, to obtain a "first flush" effect under the appropriate conditions. Stormwater pollution was not included in the model, as a simplifying assumption.

Noise is added to all generated quantities in order to reproduce the variability of the phenomena. Fig. 4 shows an example of a generated influent time series.

For more details on the phenomenological model summarised above, the reader is referred to Gernaey et al. (2005).

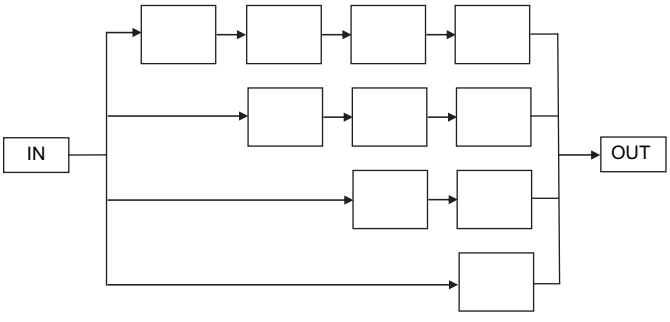

Fig. 3. Schematic representation of the sewer model.

The production of a yearly influent file with data every 15 min for a system with large sewer network takes less than 5 min on a Pentium 4 machine with a 3 GHz processor.

3. Tools for modelling and simulation

3.1. Models used

In case an immission-based evaluation of the alternative measures is required, the models of the involved sub-systems (catchment, sewer network, WWTP, river stretch) must be implemented and integrated. Each component of the system under analysis needs to be appropriately modelled and then the sub-models must be linked to be able to simulate the behaviour of the whole system. In this study, the components making up the studied system are the WWTP—composed of activated sludge tanks and settlers—and a river stretch. The sewer system is modelled by the influent data generator. More details on the models used—a slightly modified (by Gernaey and Jørgensen, 2004) Activated Sludge Model no. 2d (ASM2d; Henze et al., 2000) for the activated sludge units, the model of Takacs et al. (1991) for the secondary settler and a simplified version (by Solvi et al., 2006) of the River Water Quality Model no. 1 (RWQM1; Reichert et al., 2001) for the river stretch—can be found in Benedetti (2006).

As the focus of the illustrative case study used here is on the WWTP design, Table 1 briefly introduces the WWTP configurations that were compared in terms of different criteria with the methodology described by Benedetti et al. (2006a). They were all designed to treat 30,000 PE under Oceanic climate conditions, following the German ATV guidelines (ATV, 2000). It is an extract of a wider comparison involving all combinations of three plant sizes under four climatic conditions (see Benedetti, 2006).

3.2. Simulation software

A new modelling and virtual experimentation kernel for water quality systems has been developed in order to be able to cope with the large computational load implied by the one-year simulations of complex WWTP layouts. This kernel was named "Tornado" and it is included in the new generation of the WEST® product family (MOSTforWATER, Kortrjik, Belgium), as well as in several other products and projects. WEST (World-wide Engine for Simulation, Training and automation) is a multi-platform modelling and experimentation system (Vanhooren et al., 2003). It allows to construct models and conduct virtual experiments on any kind of system that can be represented by differential algebraic equations. The WEST simulator was originally used mainly for simulation of wastewater treatment plants and an extensive WWTP model base is available. The model base plays a central role in WEST. In this model base, models are described in a high level object-oriented declarative language specifically developed to incorporate models. The model base is aimed at maximal reuse of existing knowledge and is therefore structured hierarchically. It is to be stressed that WEST has an open structure, i.e. the user is

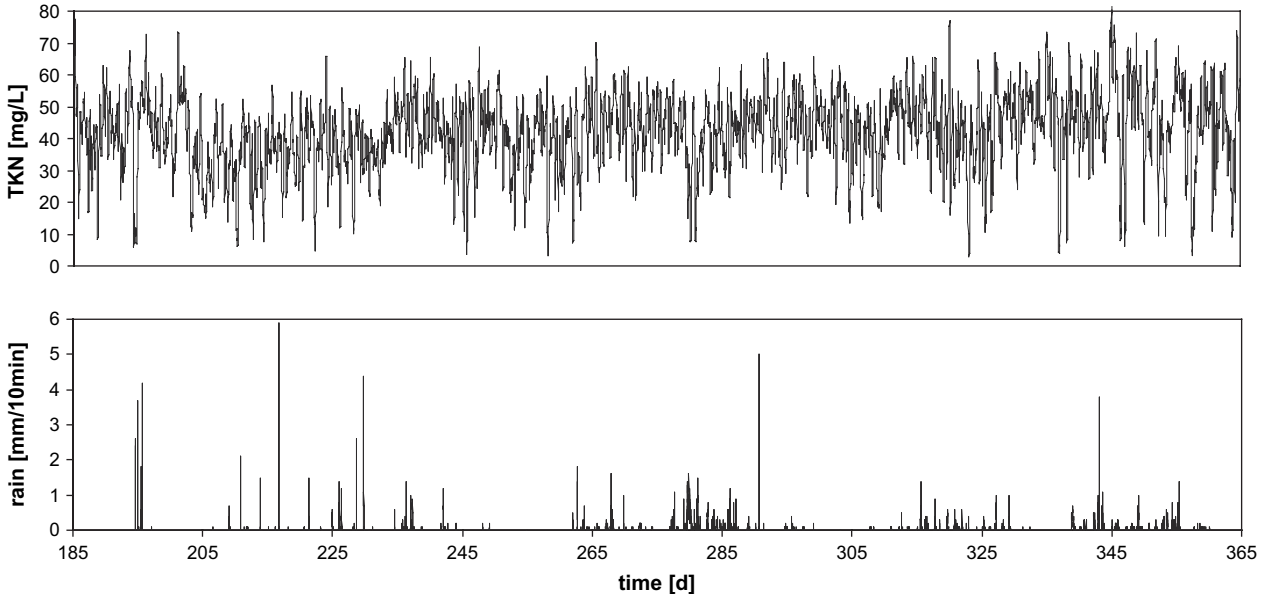

Fig. 4. Example of input (rain, bottom) and output (Total Kjeldhal Nitrogen (TKN), top) of the influent generator.

allowed to change existing models and define new ones as needed, taking full advantage of the reusability of the already existing models. Next to the wastewater treatment models, a run-off/sewer model based on KOSIM (Solvi et al., 2005) and the RWQM1 (Reichert et al., 2001) are now implemented in this package and run in simultaneous simulations mode e.g. for integrated RTC investigations (Vanrolleghem et al., 2005).

Most important issues during the development of Tornado were versatility and efficiency. It is argued that classical approaches such as the adoption of general purpose simulators, custom codes and/or domain-specific simulators all have specific disadvantages (e.g. absence of a specific model base, lack of flexibility, execution of non-compiled code). Therefore, a need arose for a kernel that offers a compromise between versatility and efficiency.

Tornado was developed in C++ using advanced language features, yielding a code base that offers fast execution, portability and increased readability. The software is composed of strictly separated environments for modelling and virtual experimentation. The modelling environment allows for the specification of complex ODE and DAE models in object-oriented, declarative languages such as MSL (Vanhooren et al., 2003) and Modelica (Fritzson, 2004). A model compiler translates these high-level models into efficient, flattened code. The experimentation environment allows for running atomic virtual experiments (such as simulations and steady-state analyses) as well as compound experiments (optimisations, scenario analyses, etc.) on the basis of flattened models. Details on Tornado can be found in Claeys et al. (2006b).

Table 1
Plant configurations

Short name	Description	COD	TN	Chem-P	Bio-P
A2O	Anaerobic-anoxic-oxic—low loaded system	X	X		X
AO	Anaerobic-oxic—high loaded system	X			X
BDNP	Biodenipho—low loaded system	X	X		X
BDN	Biodenitro—low loaded system	X	X		
HLAS	High loaded activated sludge	X			
LLAS	Low loaded activated sludge	X	X	X	
LLAS_PS	LLAS with primary settler	X	X	X	
OD_bioP	Oxidation ditch—low loaded system	X	X		X
OD_simP	Oxidation ditch—low loaded system	X	X	X	
UCT	University Cape Town—low loaded system	X	X		X

As an example of performance a low loaded activated sludge treatment system (LLAS) model (with chemical P-removal, several controllers and modified ASM2d in eight tanks, for a total of 5109 parameters (many of these having the same value), 4210 algebraic variables and 276 derivatives), running for 50 days in steady state and 415 days in dynamic conditions, with input and output data every 15 min, using WEST version 3.7.3 (which includes Tornado) required only 31 min to execute on a Pentium 4 machine with a 3 GHz processor. Using WEST version 3.7.2, it took 140 min. The reasons why Tornado performs better than WEST 3.7.2 are:

- in Tornado, overhead has been kept to a minimum. In particular, only essential operations are part of the simulator's inner loop, other operations are automatically moved by the model compiler to a section containing initialisation code (e.g. computation of conversion factors for unit conversion).
- Tornado is more configurable than WEST, which has an impact on performance since what is not needed can be switched off (e.g. unit conversion, bounds checking).
- Tornado supports executable models consisting of Initial computations, State computations, Output computations

and Final computations. Initial and Final computations are only executed once. State computations are computed at every minor time-point. Output computations are only executed at major time-points. WEST 3.7.2 on the other hand executes State and Output computations at minor time-points too.

4. Tools for uncertainty assessment

An issue when dealing with models is the uncertainty linked to their predictions. Probabilistic design, which is the combination of probabilistic modelling techniques with the currently available mechanistic models, provides a solution to this issue in the case of model-based design of a system (Bixio et al., 2002).

The adopted methodology makes use of Monte Carlo simulations (McKay, 1988) to propagate model parameter uncertainties into the model predictions and has been described in Benedetti et al. (2006a). The uncertain parameters and their probability density functions (PDFs) are listed in Table 2, and were selected according to previous studies (Reichert and Vanrolleghem, 2001; Rousseau et al., 2001). In this section the proposed probabilistic descriptors are introduced, and the methodology is evaluated concerning the convergence of the Monte Carlo (MC) simulation and the sensitivity of the results to the adopted PDFs. The software used for distributed simulations is also briefly described.

4.1. Probabilistic descriptors

Due to the large amount of data resulting from the simulations—long time series with frequent data points for each MC simulation—some user friendly way to present and summarise the data had to be devised. Below, the three main ways which were developed and used in this work are described.

4.1.1. Percentile polygons

Two examples of uncertainty visualisation are given; on the left side of Fig. 5 for each of the 10 configurations compared in the example case study, a cloud of 100 dots is plotted, each dot representing the yearly average of the effluent quality index (EQI) and of the total costs (TC) for one particular MC simulation; on the right side, each cloud is summarised by a polygon joining the 5th and 95th percentiles for the two variables and by a marker for the 50th percentile. The EQI and TC calculations are based on the Benchmark Simulation Model of Copp et al. (2002) and are used as an example of general evaluation criteria; of course, *ad hoc* evaluations can be performed for specific criteria of interest (e.g. N removal vs. energy costs). An important property of such graphs is that the larger the projection of a configuration's polygon on an axis is, the larger is the uncertainty of that configuration for the variable associated to that axis. For a description of EQI, TC and the performed data processing, please refer to Section 5.

4.1.2. Concentration–duration curves and box-plots

Another way to look at uncertainties for dynamic simulations is by means of concentration–duration curves. In contrast with yearly averages, these descriptors allow to summarise both the dynamics and the uncertainty information. From Fig. 6 (left graph) it can be deduced that with the considered plant configuration, it is 95% sure that the threshold of 15 mg L^{-1} of TN is not exceeded for more than 32% of the analysed period (one year), in case the effluent is measured by means samples every 15 min.

To be able to compare several alternatives, a threshold can be chosen, and for each alternative the statistics for the 100

Table 2
Uncertain parameters listed with their statistical properties; for an explanation of the parameters name, refer to Benedetti (2006), Henze et al. (2000) and Gernaey and Jørgensen (2004)

Name	Original PDFs					Alternative PDFs					Unit
	Probability density function (PDF)	Mean (mode)	Minimum	Maximum	Standard deviation	Probability density function (PDF)	Mean (mode)	Minimum	Maximum	Standard deviation	
f_{S_F}	Triangular	0.375	0.3	0.45	–	Uniform	–	0.3	0.45	–	–
f_{X_S}	Triangular	0.68	0.544	0.816	–	Uniform	–	0.544	0.816	–	–
μ_H	Normal	6	4.8	7.2	0.4	Triangular	6	4.8	7.2	–	d^{-1}
μ_{AUT}	Normal	1	0.8	1.2	0.067	Triangular	1	0.8	1.2	–	d^{-1}
μ_{PAO}	Normal	1	0.8	1.2	0.067	Triangular	1	0.8	1.2	–	d^{-1}
μ_H_b_H	Uniform	–	9.2	11.4	–	Triangular	10	9.2	11.4	–	–
μ_{AUT}_b_{AUT}	Uniform	–	4.6	5.7	–	Triangular	5	4.6	5.7	–	–
μ_{PAO}_b_{PAO}	Uniform	–	4.6	5.7	–	Triangular	5	4.6	5.7	–	–
η_{NO3_Hyd}	Triangular	0.6	0.48	0.72	–	Uniform	–	0.48	0.72	–	–
η_{NO3_Het}	Triangular	0.8	0.64	0.96	–	Uniform	–	0.64	0.96	–	–
η_{NO3_PAO}	Triangular	0.6	0.48	0.72	–	Uniform	–	0.48	0.72	–	–
K_{O_A}	Triangular	0.5	0.25	0.75	–	Uniform	–	0.25	0.75	–	g O_2 m^{-3}
Y_{PO}	Triangular	0.4	0.32	0.48	–	Uniform	–	0.32	0.48	–	g Pg COD^{-1}
$\eta_{NO3\_Het\_d}$	Triangular	0.5	0.4	0.6	–	Uniform	–	0.4	0.6	–	–
$\eta_{NO3\_P\_d}$	Triangular	0.33	0.264	0.396	–	Uniform	–	0.264	0.396	–	–
$\eta_{NO3\_Aut\_d}$	Triangular	0.33	0.264	0.396	–	Uniform	–	0.264	0.396		–

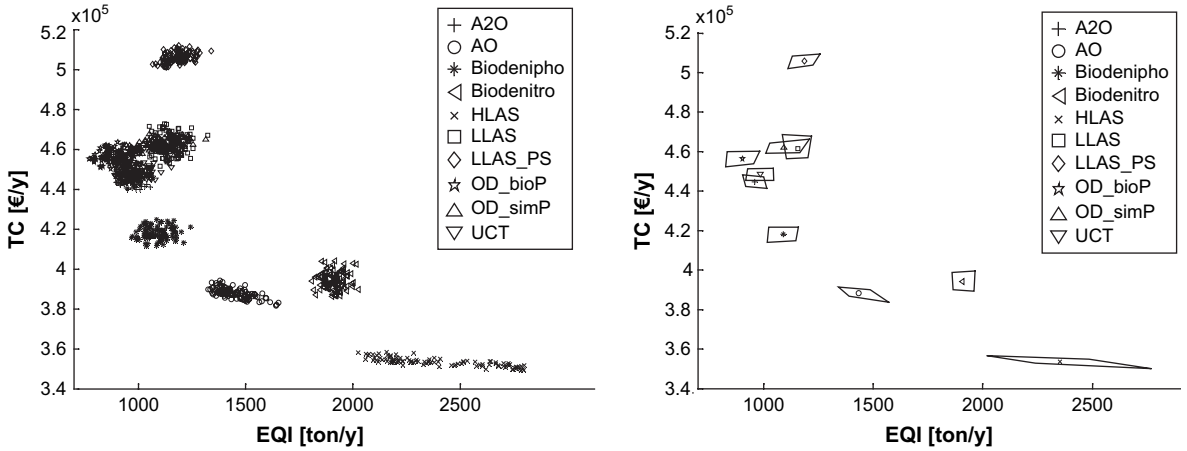

Fig. 5. Two options to visualise Monte Carlo simulation results: all results as a cloud of markers (left) and polygons joining the 5th and 95th percentiles for the two variables and the 50th percentile as a marker (right); the data show yearly average effluent EQI and TC for 10 different plant configurations.

simulations are summarised by means of box-plots, showing the percentiles relative to the exceedance period, e.g. as shown in Fig. 6 (right graph) for the above-mentioned plant configuration with the threshold fixed at 15 mg L^{-1} of TN.

4.1.3. The relative reliability index

An important criterion that has also been introduced is a measure to summarise the model output uncertainties in one number: the relative reliability index (RRI). Starting from the yearly averages of a variable (e.g. 100 values as in the left side of Fig. 5), the RRI is the average of that variable for all the configurations in the comparison divided by the standard deviation of the 100 values, to normalise the magnitude of the standard deviation. It is further normalised by dividing it by the average RRI for all configurations, so that the values of the RRI have an average of 1:

$$RRI_{X^c} = \frac{\sum_{i=1}^{n} X_i^c / n}{\sigma_{X^c}} \Bigg/ \frac{\sum_{j=1}^{p} \frac{\sum_{i=1}^{n} X_i^j / n}{\sigma_{X^j}}}{p} \quad (1)$$

where X is a variable (e.g. yearly average of COD), c is a configuration, n is the number of MC samples (100), σ_{X^c} is the standard deviation of variable X for configuration c, and p is the number of configurations (10).

It gives a measure of how stable the performance of the configuration is when it is subjected to variations in model parameters. It can be calculated for every single variable or for a combination of them (just by summing the RRIs for the studied variables), e.g. in the case of two variables, the RRI is (inversely) related to the perimeter of the polygons in Fig. 5 (right side) as can be seen in Fig. 7.

4.2. Assessment of convergence

For each combination of plant configuration, size and climate, 100 parameter combinations were sampled from the

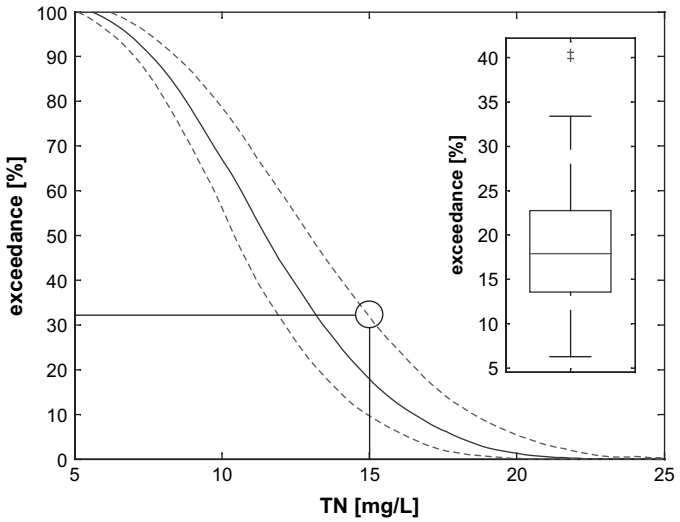

Fig. 6. Concentration–exceedance curve for LLAS, TN effluent concentrations sampled every 15 min. Full line, 50th percentile; dotted lines, 5th and 95th percentiles. The box plot on the right side refers to the exceedance of TN = 15 mg L^{-1} and shows the median, the quartiles, the 5th–95th percentiles and outliers.

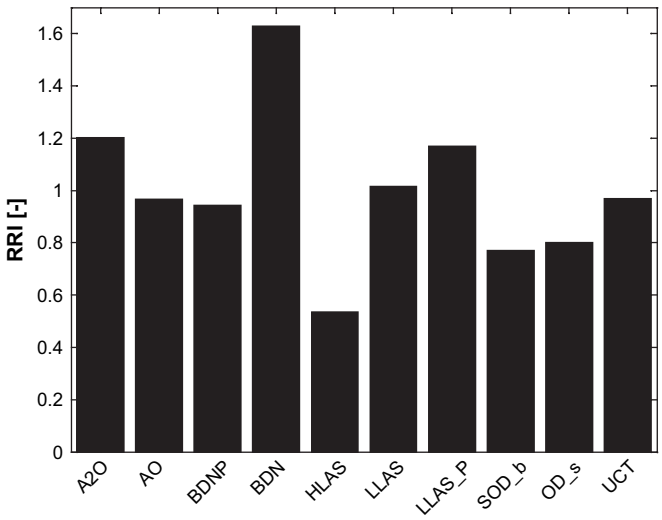

Fig. 7. RRI for the 10 plant layouts based on EQI and TC.

parameter space using Latin Hypercube Sampling (LHS) to perform the MC uncertainty assessment. This number of simulations was found to be sufficient to reach convergence of the simulation output distributions.

In Fig. 8, the convergence of the distribution of the predicted NH_4 effluent concentrations for the LLAS configuration is shown. To obtain that graph, for each of the 100 simulations the NH_4 concentration effluent time series (data each 15 min, for a total of 35,040 data points in one year) is divided into 20 concentration intervals (classes) and the occurrences (frequencies) in each class are counted (see Fig. 9 for a histogram for one of the 100 simulations). Then in each of the 20 classes the average frequency for the first i simulations is plotted against i (the lines in Fig. 8), with i from 1 to 100. When these average frequencies stabilise around some values, one can state that convergence is reached. In our case, this appears to have already happened with less than 100 simulations except for the classes in which only few occurrences accumulate (i.e. at high ammonium concentrations). The 20 classes are centred at values from 1.2 g NH_4 m^{-3} (class 1 and most frequent) to 5.1 g NH_4 m^{-3} (class 20 and least frequent).

The discontinuities—evident especially with low-frequency classes (high values of NH_4) and when only a small number of MC simulations has been accumulated (left side of the graphs in Fig. 8)—are caused by simulations which are characterised by a particularly high NH_4 average throughout the year (e.g. caused by a low nitrifier growth rate in winter). Such MC simulations strongly increase the frequency of medium and low frequency classes when the average is calculated over a small number of simulations.

4.3. Sensitivity to probability density functions

Another issue is the choice of the PDF for each of the uncertain parameters. To assess the importance of this choice of PDF, a MC uncertainty analysis was performed for the Biodenipho configuration with two different sets of PDFs (Table 2). In Fig. 10 an example of the comparison between the two MC analyses with two different PDF sets is shown.

It is evident that the alternative PDF set leads to some more uncertain outputs. This result was expected since in the alternative PDF set more uniform distributions are used than in the original set. Uniform distributions with the same minimum and maximum contain less information (more uncertainty) than triangular or normal distributions. Therefore, more uncertainty is propagated in the simulation outputs. This leads to the conclusion that care should be taken in choosing the PDFs for the MC analysis and that in case little information is available on the parameters, it is advisable to adopt uniform distributions in order not to underestimate the model prediction uncertainties.

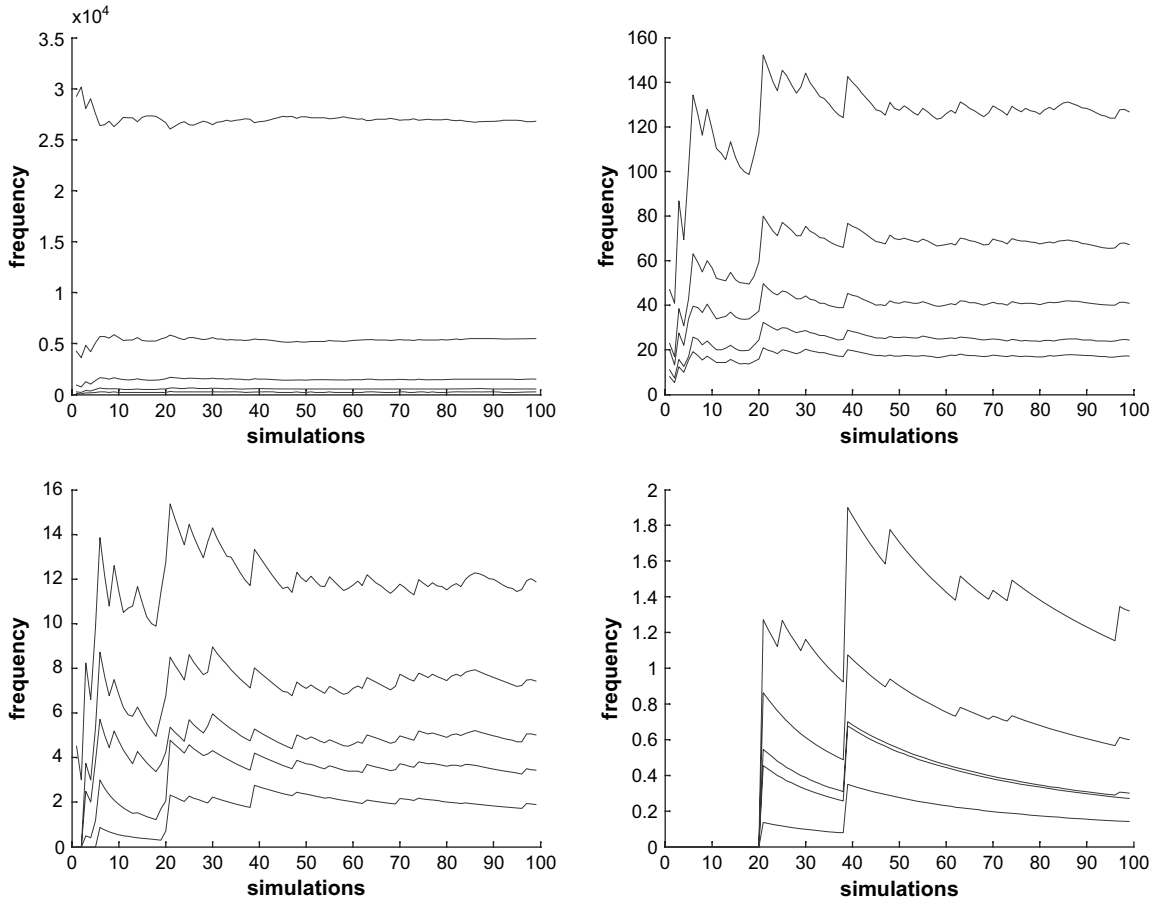

Fig. 8. Convergence for 20 classes of NH_4 output for LLAS; from left to right and from top to bottom: classes 1–5, 6–10, 11–15 and 16–20.

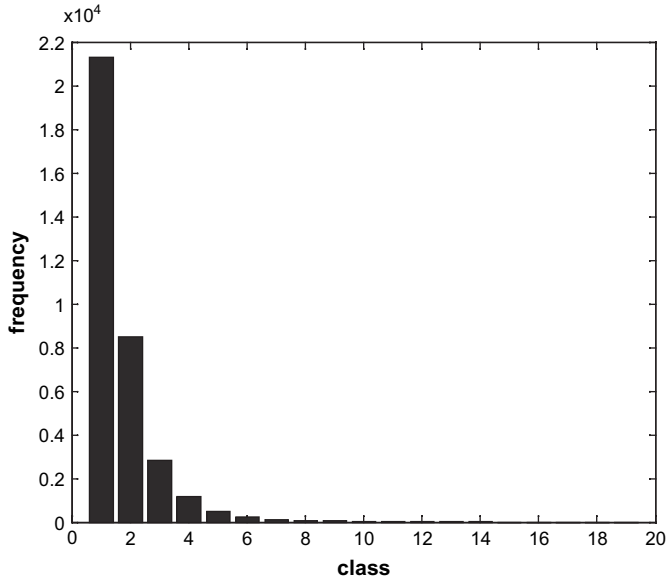

Fig. 9. Histogram for frequencies of NH_4 in one of the 100 simulations for LLAS.

4.4. Distributed simulations

The number of necessary simulations for scenario analysis tends to be large, especially with MC-based uncertainty assessment. To reduce this computational burden, tools that distribute simulations over idling PCs available in a local network are under development and were used in this study (Claeys et al., 2006a). A framework for the distributed execution of simulations on a potentially heterogeneous pool of work nodes (Linux/Windows) has been implemented. It was named ''Typhoon'' and has been built on top of technologies such as C++, XML and SOAP. It was designed for stability, expandability, performance, platform-independence and ease of use.

To show how the feasibility of the proposed methodology of probabilistic analysis is dramatically increased by the development and use of Typhoon, Fig. 11 shows the comparison of the execution of a batch of 100 MC simulations of the LLAS model with the previous version of WEST (3.7.2), with the latest version of WEST (3.7.3) which includes the new simulation kernel Tornado, and with the cluster available for this study (16 Linux machines with 3 GHz processors) using Typhoon.

It is obvious that the distribution of parallel simulations to a group of available PCs gives a major reduction in calculation time.

5. Tools for evaluation of alternatives

Water quality standards are already incorporated in most of the current legislations in most countries. The immission-based evaluation allows to identify the effect of measures on water quality and is complementary to the emission-based evaluation which is also part of the ''combined approach'' introduced by the WFD.

The comparison of alternative scenarios can be based on performance criteria that can be grouped into two categories: environmental and economic criteria. The weight attributed to them in the decision making process depends on the specific situation of the project. For both categories uncertainties are computed, and therefore risk issues can be analysed.

All evaluations of alternatives concerning environmental and economic performance as well as associated uncertainties were performed by automatic post-processing of the output files generated by all MC simulations by using Matlab scripts created *ad hoc*. Using the concept of post-processing of MC simulation data stored in files allows to perform such evaluations without the need to re-run all simulations (which is the time-consuming part of the study), but just performing again the post-processing with different values for costs and for the weights used to calculate indexes. For example, the processing of a batch of 100 MC output files of the mentioned LLAS model (each containing 12 MB of data) required 10 min to execute on a Pentium 4 machine with a 3 GHz processor.

Examples of obtained evaluation results can be found in Benedetti (2006) and Benedetti et al. (2006a,b).

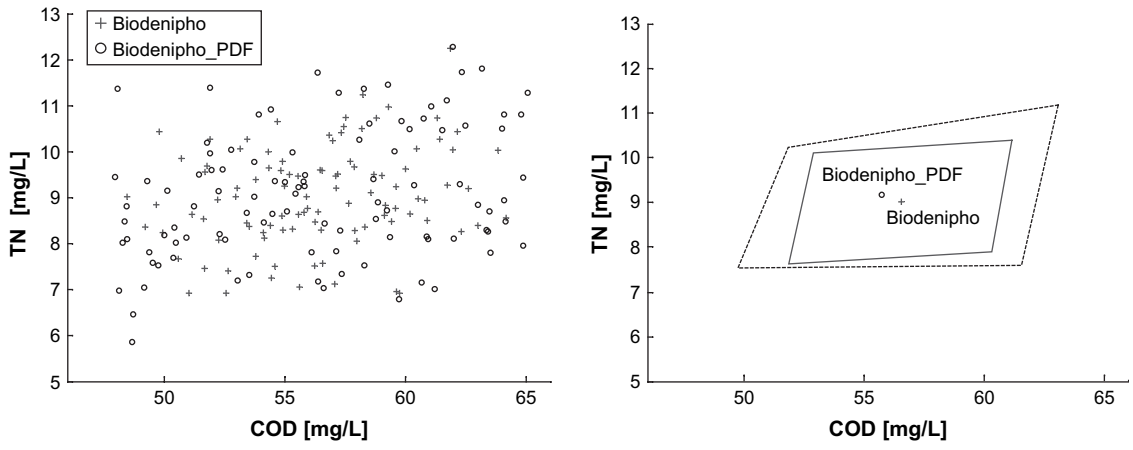

Fig. 10. COD and TN average concentrations for two different PDF sets for Biodenipho as cloud of dots (left) and as percentile polygons (right); in the legend, Biodenipho is with the normal PDF set and Biodenipho_PDF with the alternative PDF set (with dotted line for the polygon).

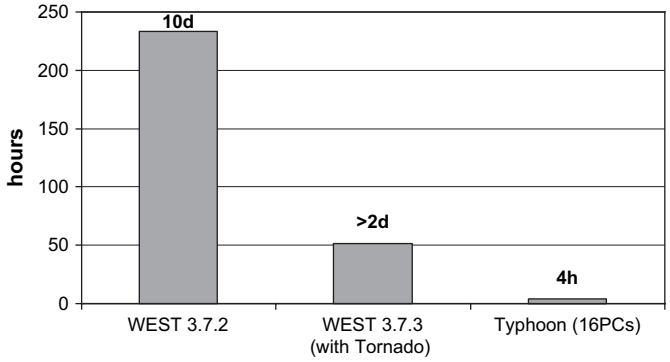

Fig. 11. Execution time for an MC experiment (100 simulations) using different tools. d, days; h, hours.

6. Conclusions

This article introduced software tools that were developed to support the use of a systematic methodology to design correction measures in urban wastewater systems, and this was illustrated by the example of WWTP design.

The generation of realistic long-term influent time series to be fed to the WWTP models is done with a new phenomenological model of the draining catchment and sewer system. One-year time series with data every 15 min are produced which realistically represent the influent dynamics with time scales varying from minutes (e.g. first flush effect) to months (e.g. seasonality in infiltration rate).

It is deemed that modelling results should always be accompanied by information on the confidence of the predictions. To deal with the large amount of simulated data generated from the long-term time series in a MC simulation context, some probabilistic descriptors were developed, namely the percentile polygons, concentration–duration curves with uncertainty bounds and the relative reliability index. The propagation of the uncertainty on model parameters was performed by means of MC simulations making use of Tornado (a new simulation kernel for the WEST software) and of Typhoon, a software tool developed to distribute the large number of MC simulations on a network of computers. Both developments dramatically reduce the simulation time necessary to apply the proposed methodology.

With the use of the innovative tools introduced in this paper it was possible to generate the probabilistic data to compare 10 plant layouts on their benefit/cost/risk in no longer than 2 days. It is therefore deemed to be of practical consideration for probabilistic design in the wider decision-making context of river basin management introduced by the WFD.

Acknowledgements

The results presented in this publication have been elaborated in the frame of the EU projects CD4WC, contract no EVK1-CT-2002-00118 and Harmoni-CA, contract no. EVK1-CT-2002-20003. P.A. Vanrolleghem is Canada Research Chair in Water Quality Modelling.

References

Achleitner, S., Möderl, M., Rauch, W., 2007. CITY DRAIN—An open source approach for simulation of integrated urban drainage systems. Environmental Modelling & Software 22, 1184–1195.

ATV, 2000. Standard ATV-DVWK-A 131E. Dimensioning of Single-Stage Activated Sludge Plants.

Benedetti, L., 2006. Probabilistic design and upgrade of wastewater treatment plants in the EU Water Framework Directive context. PhD thesis, Ghent University, Belgium, 304 p. http://biomath.ugent.be/publications/download/.

Benedetti, L., Bixio, D., Vanrolleghem, P.A., 2006a. Assessment of WWTP design and upgrade options: balancing costs and risks of standards' exceedance. Water Science and Technology 54 (6–7), 371–378.

Benedetti, L., Bixio, D., Vanrolleghem, P.A., 2006b. Benchmarking of WWTP design by assessing costs, effluent quality and process variability. Water Science and Technology 54 (10), 95–102.

Bixio, D., Parmentier, G., Rousseau, D., Verdonck, F., Meirlaen, J., Vanrolleghem, P.A., Thoeye, C., 2002. A quantitative risk analysis tool for design/simulation of wastewater treatment plants. Water Science and Technology 46 (4-5), 301–307.

CEC, 2000. Directive 2000/60/EC of the European Parliament and of the Council establishing a framework for the Community action in the field of water policy.

Claeys, F., Chtepen, M., Benedetti, L., Dhoedt, B., Vanrolleghem, P.A., 2006a. Distributed virtual experiments in water quality management. Water Science and Technology 53 (1), 297–305.

Claeys, F., De Pauw, D.J.W., Benedetti, L., Vanrolleghem, P.A., 2006b. Tornado: A versatile and efficient modelling and virtual experimentation kernel for water quality systems. In: Proceedings of the iEMSs 2006 Conference, 9–12 July 2006, Burlington, VT, USA.

Copp, J., Spanjers, H., Vanrolleghem, P.A. (Eds.), 2002. Respirometry in Control of the Activated Sludge Process: Benchmarking Control Strategies. IWA Publishing, London, UK.

Devisscher, M., Ciacci, G., Fé, L., Benedetti, L., Bixio, D., Thoeye, C., De Gueldre, G., Marsili-Libelli, S., Vanrolleghem, P.A., 2006. Estimating costs and benefits of advanced control for wastewater treatment plants—the MAgIC methodology. Water Science and Technology 53 (4-5), 215–223.

Fritzson, P., 2004. Principles of Object-Oriented Modeling and Simulation with Modelica 2.1. Wiley-IEEE Press.

Fu, G., Butler, D., Khu, S.-T., 2008. Multiple objective optimal control of integrated urban wastewater systems. Environmental Modelling & Software 23, 225–234.

Gernaey, K., Jørgensen, S.B., 2004. Benchmarking combined biological phosphorous and nitrogen removal wastewater treatment processes. Control Engineering Practice 12, 357–373.

Gernaey, K., Rosen, C., Benedetti, L., Jeppsson, U., 2005. Phenomenological modelling of wastewater treatment plant influent disturbance scenarios, In: Proceedings of the 10th International Conference on Urban Drainage (ICUD), 21–26 August 2005, Copenhagen, Denmark.

Henze, M., Gujer, W., Mino, T., van Loosdrecht, M.C.M., 2000. Activated Sludge Models ASM1, ASM2, ASM2d and ASM3. IWA Publishing, London, UK.

McKay, M.D., 1988. Sensitivity and uncertainty analysis using a statistical sample of input values. In: Ronen, Y. (Ed.), Uncertainty Analysis. CRC Press, Boca Raton, FL, pp. 145–186.

Ráduly, B., Gernaey, K.V., Capodaglio, A.G., Mikkelsen, P.S., Henze, M., 2007. Artificial neural networks for rapid WWTP performance evaluation: Methodology and case study. Environmental Modelling & Software 22, 1208–1216.

Reichert, P., Vanrolleghem, P.A., 2001. Identifiability and uncertainty analysis of the River Water Quality Model No. 1 (RWQM1). Water Science and Technology 43 (7), 329–338.

Reichert, P., Borchardt, D., Henze, M., Rauch, W., Shanahan, P., Somlyódy, L., Vanrolleghem, P., 2001. River Water Quality Model no. 1 (RWQM1): II.

Biochemical process equations. Water Science and Technology 43 (5), 11–30.

Rivas, A., Irizar, I., Ayesa, E., 2008. Model-based optimisation of Wastewater Treatment Plants design. Environmental Modelling & Software 23, 435–450.

Rousseau, D., Verdonck, F., Moerman, O., Carrette, R., Thoeye, C., Meirlaen, J., Vanrolleghem, P.A., 2001. Development of a risk assessment based technique for design/retrofitting of WWTPs. Water Science and Technology 43 (7), 287–294.

Solvi, A.-M., Benedetti, L., Gillé, S., Schlosseler, P., Weidenhaupt, A., Vanrolleghem, P.A., 2005. Integrated urban catchment modelling for a sewer-treatment-river system in Luxembourg. In: Proceedings of 10th International Conference on Urban Drainage (ICUD), Copenhagen, Denmark, 21–26 August 2005.

Solvi, A.-M., Benedetti, L., Vandenberghe, V., Gillé, S., Schlosseler, P., Weidenhaupt, A., Vanrolleghem, P.A., 2006. Implementation of an integrated model for optimised urban wastewater management in view of better river water quality: A case study. In: Proceedings of IWA World Water Congress 2006, 10–14 September. Beijing, China.

Takacs, I., Patry, G.G., Nolasco, D., 1991. A dynamic model of the clarification-thickening process. Water Research 25 (10), 1263–1275.

Vanhooren, H., Meirlaen, J., Amerlink, Y., Claeys, F., Vangheluwe, H., Vanrolleghem, P.A., 2003. WEST: Modelling biological wastewater treatment. Journal of Hydroinformatics 5 (1), 27–50.

Vanrolleghem, P.A., Benedetti, L., Meirlaen, J., 2005. Modelling and real-time control of the integrated urban wastewater system. Environmental Modelling & Software 20, 427–442.