Probabilistic emission and immission modelling:
case-study of the combined sewer – WWTP – receiving
water system at Dessel (Belgium)

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Abstract The impact of the combined urban drainage and WWTP system of the village of Dessel (Belgium) on the Witte Nete receiving water is modelled both in terms of emissions and immissions. The hydrodynamic and water quality modelling is performed both in a deterministic and probabilistic way. For the deterministic modelling, detailed physically based and simplified conceptual models are used in a complementary way. In the probabilistic modelling, the different uncertainties in the deterministic model are classified in input uncertainties, parameter uncertainties and model-structure uncertainties. The probabilistic simulation results can be used in risk analysis and management, for the determination of the major uncertainty-sources and priorities in model improvement, for model bias elimination and for efficient model calibration.

Keywords Receiving waters; sewer system; uncertainty analysis; urban drainage

Introduction

To model the flow and water quality impact of an urban drainage system on the receiving water course, both systems have to be modelled in an integrated way together with the other sources of water and pollution. The different physical and natural subsystems that are connected to all these sources have to be linked in a holistic model. An overview of these subsystems is given in Figure 1, together with the different modelled processes.

Holistic immission modelling, despite its interest, has been rarely used except for simulations over a short period of time (e.g. Crabtree et al., 1996; Fronteau, 1999; Mark and Williams, 2000). This is due to two fundamental problems. First of all, most frequently applied models cannot be used for the different subsystems in the holistic model. They are too sophisticated and the linking of many sophisticated models leads to unacceptably large calculation times and memory needs. Secondly, the uncertainty in the holistic model results may be very high because of the large extent of the model. It is therefore necessary to take the uncertainties involved in the modelling into account.

In the study presented, a modelling methodology is applied which uses simplified (but partly physically based) models for the different subsystems and processes involved: water courses, urban drainage system, watershed runoff, agricultural and industrial pollution sources. The simplified models have both a hydrodynamic and water quality description, and are applied in a complementary way to the more frequently used detailed system models. The (physically based and transparent) calibration of the simplified models is based on available measurements and/or the detailed models. To quantify the different uncertainties, which are classified in input-, parameter- and model-structure uncertainties, a step-wise procedure is followed. All uncertainty-sources are represented by stochastic terms, which transfer the holistic and simplified deterministic model to a probabilistic one.

For some of the submodels and uncertainty-sources, uncertainty studies have been previously performed (e.g. Beck, 1987; Lei and Schilling, 1996). A systematic quantification of the three main uncertainty components (input-, parameter- and model-structure uncertainties) has however not been done to date. The decomposition of the total uncertainty into
its components allows separating of inherent variability that cannot be removed (even with an exact model) and controllable variability that can be removed either by collecting more data or by using a more sophisticated model. Knowing the size of these different components is essential to an objective choice of the model detail.

**General modelling methodology**

For reasons of accuracy, the study starts from detailed physically based models for the different subsystems. Such subsystems are however not always available and appropriate. Referring to the problem of overparameterization (see e.g. Jakeman and Hornberger, 1993), detailed physically based models can often only be built in an accurate way whenever a large amount of spatial data is available. For a full hydrodynamic sewer system model, for instance, geometric data of all sewer pipes is needed. For a spatially distributed hydrological model, as another example, spatial data of land use and soil characteristics should be available.

Detailed data is however often only available for the hydrodynamic description of sewer systems and rivers. Therefore, only for these subsystems are detailed physically based models appropriate in most case-studies. For the other subsystems, conceptual or empirical models have to be built and calibrated directly. This is often the case for storage sedimentation basins, biological treatment of WWTPs, pollutant washoff from sewer system catchments, catchment runoff and nitrate leaching. For these systems and processes, two possibilities exist. An accurate conceptual model can be built and calibrated whenever sufficient data is available both for the input and output variables of the model. If this is not the case, a less accurate conceptual or empirical model has to be used. Such a model should be very parsimonious. Only the most dominant processes should be described by using only a few parameters.

In the probabilistic modelling methodology, the different uncertainty-sources involved in

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**Figure 1** Schematic overview of the different subsystems and modelled processes in a combined sewer – WWTP – river system model
the deterministic modelling are estimated in a step-wise way. First, the model-input uncertainties are quantified in an independent way. For the most important input variable, the rainfall input, this uncertainty consists of measurement errors and estimation uncertainty. The latter uncertainty is the error in the estimation of spatially averaged rainfall on the basis of rain gauge data. It was quantified by analyzing a large amount of spatial rainfall data.

Also the parameter uncertainties can be quantified in an independent way. For measured parameter values, the parameter uncertainties equal the measurement errors. For parameter values estimated on the basis of experience, they correspond with estimation uncertainties (also assessed on the basis of experience). For the calibrated parameters, parameter uncertainties are derived on the basis of regression theory.

After quantification of the model-input and parameter uncertainties, the contribution of these uncertainties to the uncertainty in the model results is quantified on the basis of random simulations with uncertain input and parameters. By comparing the uncertain model output with available measurements, the contribution of the model input and parameter uncertainties to the total uncertainty in the model-output variables (as observed by the model residuals) is quantified after subtraction of the measurement errors. The remaining uncertainty is considered as the sum of the model-structure uncertainties and they are quantified first for the flow and upstream submodels. In this way, they can be quantified for the different subsystems in a step-wise way.

**Case-study**

**System description**

The different steps of the methodology are implemented for the case-study of the combined sewer – WWTP system at the village of Dessel (Belgium). This system has a total area of 492.8 ha and 12,376 population equivalents. In the single WWTP downstream of the system (Figure 2), the sewage is biologically treated up to a discharge of 100 l/s. Higher discharges are stored and treated in a rain water storage tank and a storage sedimentation tank (SST). The overflow discharges of the SST and the effluent discharges of the biological treatment confluence in the effluent canal of the WWTP. They are discharged into the Witte Nete receiving water.
The impact of the combined sewer – WWTP system on the Witte Nete river is modelled both in terms of emissions and immissions. For model calibration and validation, discharge data are available for the downstream sewer pipes and downstream in the receiving water (Figure 2). Water quality data are available from the emission measuring-network of the Flemish Environmental Agency (VMM) and a more extensive measuring-campaign at the WWTP. This measuring-campaign was part of a Flemish inter-university project on “Ancillaries to sewer system overflows”, supported by the Flemish authorities AMINAL and VMM. The water quality data consist of concentrations and loads for total suspended solids (TSS), settleable solids (SS), BOD and ammonia (NH$_4^+$-N). Due to limitations in the sampling device, only twelve 10 min averaged samples were taken per (overflow) event.

**Deterministic modelling**

To model the hydrodynamics of the sewer network and the river system, complementary use is made of detailed physically-based and simplified conceptual models. For the sewer system, an existing full hydrodynamic model, implemented by the Flemish water treatment company Aquaflin is used as a detailed model. It is an implementation of the modelling system Hydroworks (Wallingford Software). With focus on the accurate description of the WWTP influent and SST overflow discharges, a conceptual multi-linear reservoir model is calibrated as a simplified model to the Hydroworks model by Vaes et al. (1998).

For the river network, an implementation of the river modelling package MIKE11 (Danish Hydraulic Institute) is made for a full hydrodynamic, advection-dispersion and water quality modelling. The Witte Nete river is modelled over its total length, together with the three most important tributaries. Assuming default values for the parameters of the water quality processes, reasonable results are achieved for the pollutant concentrations measured approximately 150 m downstream of the WWTP. As a simplified model, a reservoir cascade model is calibrated for the river flow upstream and downstream of the WWTP and an equivalent continuous stirred tank reactor (CSTR) model for the water quality description.

To allow an accurate immission modelling, also the river catchment upstream of the WWTP is modelled (total area of 40 km$^2$), taking into account the major sources of water and pollution. The major source of agricultural pollution, the nitrate leaching in the catchment, is modelled in a physically based way. The Drainmod modelling system (North Carolina State University) is implemented and calibrated by El-Sadek et al. (2000). Although this model is only valid on a single percal scale, it is used in a regional catchment modelling application by averaging the nitrate leaching results for a large number of percas with different land use, crop type and soil characteristics. The results are used as input for the river water quality model.

For the other subsystems and processes (pollution washoff, storage sedimentation basin, biological treatment WWTP, catchment runoff) conceptual or empirical models are built and calibrated.

For the rainfall-runoff in the hydrographic catchment, an accurate conceptual model is calibrated to the limnigraphic data downstream of the catchment. A physically based stepwise calibration procedure is used for this purpose.

To model the treatment efficiency of the SST (by storage and sedimentation), the existing model of De Cock et al. (1998) is applied. This model is partly conceptual, partly empirical and derived from a large number of laboratory experiments. It is based on the calculation of the residence time for each “plug” which enters the basin. During that time, advection and dispersion occurs, together with settling of the pollution particles. The settling efficiency is calculated on the basis of the settling velocity of the particles by an empirical formula (Vaes et al., 1999). To validate the model, a comparison is made between the measured and mod-
elled TSS and SS loads at both the influent and effluent of the WWTP for six overflow events during the measuring-campaign of the inter-university project. The SS concentration measurements can be used for validation of the storage part of the model, while the TSS measurements are used for validation of the sedimentation model. Good results are achieved without model calibration (see later).

For the washoff and sewer transport of pollutants, the biological treatment efficiency and the other pollution sources in the catchment (upstream, untreated domestic and industrial pollution sources), very parsimonious and less accurate models are built. Detailed physically based models are not feasible because of large limitations in the availability of water quality data to be used as input and for calibration of such models (see also Ashley et al. (1999) and Harremoës and Madsen (1999)). For the simplified modelling of the washoff and sewer transport of pollutants, the model of Bechmann (1999) is implemented. In this model, both processes are described in a combined way:

\[
\text{washoff} = \frac{dx}{dt} = \frac{1}{k_1} (x \cdot x^*) + b(Q \cdot Q^*) \quad \text{if} \quad \frac{dx}{dt} > 0
\]

\[
= 0 \quad \quad \quad \text{if} \quad \frac{dx}{dt} \leq 0.
\]

In this model, the total pollution deposit (on the street surfaces and in the sewer pipes) \(x\) grows by surface deposition and sedimentation in the sewer pipes during periods with dry weather flow conditions \((Q < Q^*)\). It decreases by washoff and erosion due to high stormwater discharges \((Q > Q^*)\). Model calibration (of the parameters \(k_1\) and \(b\)) is based on the influent measurements of the water quality parameters TSS, SS, BOD and NH\(_4\)\(^+\)N for six rainstorm events during the inter-university measuring campaign.

The biological treatment efficiency of the WWTP is empirically modelled on the basis of the VMM emission measurements, using a constant treatment efficiency depending on the water quality variables under study. The measurements are limited to approximately 30 samples per year (simultaneous measurements at the influent and effluent of the WWTP).

**Probabilistic modelling**

Based on the linked simplified model for all these processes and subsystems, long-term simulations are performed with historical point rainfall data (1986–1997). Model residuals are calculated for the periods with flow and water quality measurements, and used in the uncertainty analysis. For each submodel, model input, parameter and model-structure uncertainties are quantified. An example of results in the uncertainty analysis is given in Figure 3 for the sewer flow model. In this figure, modelled and measured cumulative volumes during different rainfall event periods are compared for the downstream sewer discharges. These volumes equal the WWTP influent volumes as no emergency overflow occurred during the measuring campaign.

Also the differences between the simulation results with the simplified reservoir model and the detailed Hydroworks model are represented in Figure 3. These differences allow us to quantify the model-structure uncertainty due to the large simplification of the sewer flow model. Another uncertainty-source that is indicated in the figure is the spatial variability of the rainfall over the sewer catchment. By assuming the spatially averaged rainfall equal to the measured point rainfall, this spatial variability is ignored in the model. The influence is studied using a spatial rainfall generator (Willems, 1999). Different spatial storms are synthetically generated and the differences between catchment-averaged rainfall and point rainfall at the rain gauge location are calculated. These differences are represented in Figure 3. Together with the rainfall measurement errors, they explain the rainfall-input uncertainty of the combined sewer – WWTP model.
On the basis of laboratory tests on the discharge monitors, also the discharge measurement errors are estimated. They are represented in terms of 68% confidence intervals on the model residuals in Figure 3. After consideration of the three mentioned (and separately quantified) uncertainty-sources, the remaining uncertainty can be considered as remaining model-structure uncertainty. In this case, it equals the model-structure uncertainty of the Hydroworks model. The simple rainfall-runoff model that is included in this model explains a large part of this uncertainty.

By the same procedure, also the model-structure uncertainties of the sewer washoff model, the biological treatment efficiency model, the SST model, the river rainfall-runoff model and the river water quality model are quantified.

Results and conclusions

In Figure 4, an example is shown of the probabilistic simulation results for hourly averaged TSS loads in the effluent of the combined sewer – WWTP system. For BOD loads, the impact on the receiving river is shown in Figure 5. The 95% two-sided confidence intervals represent the total uncertainty in the model results. The effluent measurements are plotted both for 10 min and hourly averaged values. The results and measurements are shown for the six overflow events measured during the inter-university measuring campaign.

Based on an analysis of the contribution of the different uncertainty-sources to the total uncertainty in the model results, priorities are determined in the study for model improvement and future research in the field of integrated urban drainage modelling. The (spatial) rainfall input and the water quality models (of both the sewer and river systems) have shown to be the major sources of uncertainty in the immission results. For the flow models (of the sewer, WWTP and river subsystems), the uncertainty contribution is rather small. This is explained by the large amount of data that is frequently available for implementation of an accurate detailed physically based flow model (full hydrodynamic model). This data consists of continuous flow data and detailed geometric system data. Using a knowledge- and physically based calibration procedure, also an accurate simplified conceptual model can be calibrated to the detailed flow models. In this way, accurate long-term flow simulations can be performed. For the water quality description, accurate detailed and simplified models cannot be constructed. Current water quality data are too limited (no continuous series of water quality measurements in the sewer system and river). Finally, by increasing the
accuracy of the rainfall input, a large increase in the accuracy of the model results can be gained. This can be done mainly by accounting for the spatial variability of the rainfall input for the different subsystems involved. Because of the large variation in spatial scale and the distances between these systems, the spatially averaged rainfall input volumes may vary considerably. This was shown in Figure 3 for the sewer system flow.

Besides determining priorities for model improvement, the probabilistic modelling results can also be used for risk analysis and risk management. Whenever the model results are used in decision-making or for engineering designs, the probability of inconsistent decisions/designs can be assessed. After quantifying the consequences of inconsistent decisions/designs, also the risk can be quantified. Contradictory to probabilistic modelling, in which only technical aspects are involved, also social and economical aspects have to be involved in the quantification of the consequences. By limitation of the risk to an acceptable risk-level (which is also defined on the basis of social and ecological aspects),
economic aspects by weighing out both “safety” and costs), designs/decisions are obtained which may be considered “sufficiently safe”.

Besides these features, probabilistic modelling has shown some more advantages during the study. It was seen that modelling which includes uncertainty analysis will lead to much more accurate (deterministic) models. Indeed, during the probabilistic modelling procedure, biases are often identified in the deterministic model as differences between the modelled values and the median values of some state-variables in the model. Based on these biases, the model can be adjusted in order to curtail the biases and to represent the physical reality in a far more adequate way.

Moreover, it was shown that calibration of model parameters becomes less problematic when the uncertainty structure of the model-output variables is known. Indeed, during the calibration the highest weights can be given to the most accurate model-output values. Maximizing the “likelihood function” of model-output, most likely (or statistically optimal) parameter values are derived.

Illustrations of these conclusions and a more detailed description of the case-study results can be found in the recent doctoral thesis of Willems (2000).

References