Optimization of measurement campaigns for calibration of a conceptual sewer model
M. Kleidorfer, M. Möderl, S. Fach and W. Rauch

ABSTRACT

To simulate hydrological models of combined sewer systems an accurate calibration is indispensable. In addition to all sources of uncertainties in data collection due to the measurement methods itself, it is a key question which data has to be collected to calibrate a hydrological model, how long measurement campaigns should last and where that data has to be collected in a spatial distributed system as it is neither possible nor sensible to measure the complete system characteristics. In this paper we address this question by means of stochastic modelling. Using Monte Carlo Simulation different calibration strategies (selection of measurement sites, selection of rainfall-events) and different calibration parameters (overflow volume, number of overflows) are tested, in order to evaluate the influence on predicting the total overflow volume of the entire system. This methodology is applied in a case study with the aim to calculate the combined sewer overflow (CSO) efficiency. It can be shown that a distributed hydrological model can be calibrated sufficiently when calibration is done on 30% of all existing CSOs based on long-term observation. Event based calibration is limited possible to a limited extent when calibration events are selected carefully as wrong selection of calibration events can result in a complete failure of the calibration exercise.

Key words | calibration, combined sewer systems, hydrological model, measurement campaigns, Monte Carlo simulation

INTRODUCTION

In order to predict the behaviour of urban drainage systems (or parts thereof) hydrological and hydrodynamic models can be applied likewise. Owing to the complexity of hydrodynamic calculations it is evident that the computation of the system’s dynamics over long periods can easily amount to large computing time. In contrast, a hydrological model is fast due to more simplified calculation methods (Rauch et al. 1998, 2002). Therefore, the use of a hydrological model is an obvious choice for certain modelling tasks—in this context especially when determining CSO performance. However, the use of a hydrological model implies that 1) model building can be accomplished in sufficient short time and 2) the model can be calibrated accurately. In this paper we approach these questions in a systematic methodology based on Monte Carlo simulation.

To obtain realistic modelling results it is impossible to use a hydrological model as a black-box-system. An accurate calibration is obviously a must. To accomplish a sufficient calibration it is necessary to understand which input parameters influence the results in which way. But when is a hydrological model calibrated sufficiently?

One of the main problems in calibrating a hydrological model of urban drainage systems is the availability and the accuracy of data. Input variables as rainfall measurements are basic requirements for simulation and thus have to be collected by all means. Model parameters as concentration time or catchment area have to be determined during...
calibration. Data on system performance (e.g. number of CSO overflows, CSO overflow volume, runoff to the wastewater treatment plant, etc.) is additionally needed for the calibration. If not available due to regular observations, such data is usually collected by arranging measuring campaigns over a relatively short time period at selected points in the sewer system. Such data collection is time consuming as well as costly for the operator. Much work has been done on calibration (e.g. Kanso et al. 2003; Madsen 2003; Mourad et al. 2005; Kavetski et al. 2006; Thyer et al. 2006; Frost et al. 2007) and uncertainty of urban storm water models (e.g. Lei & Schilling 1996; Bertrand-Krajewski et al. 2003; Kanso et al. 2005; Korving & Clemens 2005; Kuczera et al. 2006).

Although having the various findings available, the calibration and optimization of measurement campaigns remains a complex task. With the aim to give guidelines for an effective calibration the following questions arise:

- What type of and how many measurements (locations and duration) are required for a sufficient calibration of hydrological sewer models?
- How reliable for long time period prediction is a model calibrated on single events compared to a model calibrated on long-time performance?
- How reliable is a model calibrated for measurement A when using it for predicting the output variable B?

It is neither possible nor reasonable to measure the complete system performance (i.e. all points of model output variable). The question arises if a model that is calibrated for a specific type of system performance (e.g. runoff volume to the treatment plant) can sufficiently predict other aspects of system performance (e.g. overflow volume). Hence, it is investigated what and how many measurements are necessary for providing a sufficient information content to predict reliably the overall system behaviour.

**METHODS**

The complex procedure of calibration of distributed hydrological models can be analysed hardly based only on real world data due to data availability. To analyse calibration and measurement campaigns in a structured way on real data, a complete dataset of measurements on all possible sites would be necessary. Because such data never is available, a different approach was chosen in this work. It is based on two real world case studies which already are calibrated on limited measurement data. These two models are regarded as baseline models assuming a “perfect” calibration. Artificial systems which should reflect uncalibrated systems are created by varying typical uncertain parameters within a specific range using Monte Carlo Simulation. This procedure has the advantage that all required “measurements” can be taken from the model calibrated. Consequently, several influences are neglected as measurement uncertainties, spatial rain distribution, model structure uncertainties and deviations from reality due to simplification. Hence, the calibration of the artificial systems is analysed focused on type and number of measurements.

**Model description**

In this work simplified hydrological models of two real world case studies in Austria (Vils and Innsbruck) were used. The use of two systems makes the results less case specific. The existing hydrological models—which have been calibrated earlier (Kleidorfer et al. 2006; Möderl 2006)—are treated as baseline models assuming a “perfect” calibration.

Both sewer systems are located in Tyrol, which is a federal state in Austria. While Vils is a rural region including areas of separate sewer systems with on-site infiltration of stormwater, Innsbruck is an urban area drained completely in combined sewers. The climate is alpine, so the region is characterized by cold winters and summers with intense rainfalls.

For the simulation the open source software City Drain (Achleitner et al. 2007) was used. City Drain is based on Matlab/Simulink with the advantage of easy pre- and post processing in the Matlab environment.

**Stochastic generation of uncalibrated systems**

Based on the models calibrated artificial systems are created by running a plain Monte Carlo Simulation. The parameter variation follows a uniform distribution with the variation range specified in Table 1 and the mean value taken from
the system calibrated. The variation range expresses data uncertainties presented in the literature (Lei 1996; Hoppe 2006; Hoppe & Gruening 2007).

For the Monte Carlo simulation the input parameters of each element are varied independently within their range and without any consideration of interdependencies between them. As the aim of the Monte Carlo simulation is not propagation of real data uncertainties on simulation results but only the generation of artificial uncalibrated systems, a parameter variation following this approach is sufficient.

This procedure assures a realistic noise due to data uncertainties and not a general over- or underestimation of simulation results in one variation-run. As the two baseline models are regarded as reference models, uncertainties due to simplifications, like spatial rain distribution, are not taken into account.

When varying CSO structure volume ±50% and controlled CSO outflow ±20% one has to take into account that this includes not only uncertainties due to insufficient building plans, but also calibration uncertainties related to simplifications, especially with regard to the hydraulic behaviour of the CSO throttle. Usually during model building several CSOs are combined to one single with consequences for the CSO storage volume and the throttle capacity. Furthermore the inline storage capacity of the sewers has to be considered. Therefore the CSO storage volume and the throttle capacity cannot be determined directly by the system’s characteristics. Instead those parameters have to be determined by calibration.

Using this methodology more than 16,000 artificial systems are produced and simulated for a one-year period for both case studies.

The duration of computation for all variations would be 2.7 years on a single 2.2 GHz processor. Using a computer-cluster with 22 dual processor nodes the variations were simulated in several weeks.

### Analysis of calibration strategies and measurement campaigns

Generally two types of measurement data can be differentiated: Long-time data as a result of continuous monitoring and short-time data as a result of measurement campaigns. For both types the total overflow volume is used as performance indicator of calibration quality. Hence, several calibration strategies based on different types of measurements (e.g. number of overflow, overflow volume, flow retained in system etc.) are tested by evaluating the deviation of the total overflow volume of the Monte Carlo simulations with the real world system using the following equation:

\[
\Delta V_{of} = \frac{\sum V_{of, measured} - \sum V_{of, simulated}}{\sum V_{of, measured}}
\]

with

\[
\Delta V_{of} = \text{deviation of overflow volume}
\]

\[
V_{of, measured} = \text{measured overflow volume}
\]

\[
V_{of, simulated} = \text{simulated overflow volume}
\]

This method shows how calibration performance increases (i.e. deviation of overflow volume decreases) with a rising number of calibration sites. This equation can also be used to assess how many measurement sites are needed for a sufficient model calibration. This also includes the question how to determine relevant measurement sites, why additionally several types of site-selections are tested. Below the effects of different calibration strategies are shown. In the diagrams the deviation of total overflow volume is drawn on the y-axis and the percentage of the measurement sites used for calibration on the x-axis.

### Table 1 Variation of input parameters

<table>
<thead>
<tr>
<th>Input parameter</th>
<th>Variation range (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dry weather flow</td>
<td>± 50</td>
</tr>
<tr>
<td>Sewer flow time</td>
<td>± 25</td>
</tr>
<tr>
<td>CSO structure volume</td>
<td>± 50</td>
</tr>
<tr>
<td>CSO controlled outflow</td>
<td>± 20</td>
</tr>
<tr>
<td>Pumping station basin volume</td>
<td>± 50</td>
</tr>
<tr>
<td>Pump rate</td>
<td>± 10</td>
</tr>
<tr>
<td>Catchment area</td>
<td>± 15</td>
</tr>
<tr>
<td>Percentage of imperviousness</td>
<td>± 30</td>
</tr>
<tr>
<td>Initial loss</td>
<td>± 50</td>
</tr>
<tr>
<td>Permanent losses</td>
<td>± 25</td>
</tr>
<tr>
<td>Time of concentration</td>
<td>± 30</td>
</tr>
</tbody>
</table>
RESULTS

Long time calibration

For calibration on long-time performance the period observed is one year. Figure 1 shows the results when calibrating on overflow volume for a calibration accuracy of 10% (i.e. one CSO is regarded as calibrated when the deviation of overflow volume is less than 10%). On the left side the CSOs are ordered by the overflow volume of the system calibrated. Hence, the first CSO used for calibration is that one with the highest discharge. On the right side the CSOs are arranged in the order of catchment area connected.

As one may see in Figure 1a measurements of 30% (Innsbruck) to 50% (Vils) of all CSOs suffice to reach an overall deviation of less than 10%. This is the best possible calibration that can be reached when allowing a maximum deviation of 10% at each CSO. Furthermore, an exceeding number of measurement sites does not improve calibration performance anymore. Figure 1b shows the results for CSO selection depending on impervious area allocated. Although the deviation of the overall overflow volume is higher (20%) after the same percentage of measurement sites the calibration aspired is reached.

Often the exact overflow volume is unknown or rather difficult to measure, thus the number of overflows is used as performance indicator for calibration (Figure 2).

Using number of overflows measurement campaigns at 80% to 90% of the CSOs are required to achieve a total overflow deviation of 19% for Innsbruck and 30% for Vils, which is still worse than calibrating on overflow volume. Again the kind of selection of CSOs for calibration (overflow volume—Figure 2a versus area allocated—Figure 2b) seems to have low influence on the results.

Event based calibration

If calibration data is not available, data is usually collected by arranging measuring campaigns at selected points in the sewer system. Such campaigns usually are limited in time and it is an essential question how long the measurement period should last to collect enough data for a sufficient calibration. Respectively not the total time period of the measurement campaign but number and character of recorded rainfall events in that time period are important. Based on analysis of historical rainfall data (which is usually available) the measured rainfall events can be classified to see whether enough (or suitable) events have been recorded.

Below calibration on five events is exemplified for three types of rainfall event selection. The calibration performance again refers to calibration on overflow volume with a selection of measurement sites depending on single overflow volume. As this is the best possible calibration strategy calibration on number of overflow events is expected to be less effective but still possible. Additionally the effects of a random event selection are shown to illustrate how a wrong (or careless) event selection impacts the deviation of total overflow volume.
Figure 3a shows how calibration improves with number of measurement sites when calibrating on that five rainfall events which contain the highest intensity peak (mm/5 min). In case of Innsbruck at about 60% of the possible sites have to be measured, in case of Vils 85% are necessary, in order to reach a deviation of 10%. When calibrating on that five rainfall events with the longest duration in the simulation period (Figure 3b) 50% to 60% of the sites have to be observed. This is similar to the results of calibration on long-time performance. To give an idea how an unsuitable event selection can influence calibration performance Figure 3c illustrates the worst results when calibrating on five randomly selected events. For this purpose five events are sampled out of a basic set of rainfall events which contain 50% of the events with highest event volume. The procedure was repeated for 60 times due to representative sample and the worst deviation was calculated. As shown, the deviation of total overflow volume is still larger than 75% even when calibration on all possible sites. Thus, a proper selection of calibration events is crucial.

Application in a case study

As case study again a hydrological model of Innsbruck was used. The aim was to calculate the sewer system performance following Austrian guiding rules (ÖAW- RB 19, 2007). This approach is described and discussed in
(De Toffol 2006 and Engelhard et al. 2008). As the sewer system performance \( \eta \) is a parameter which directly expresses total overflow volume, the methodology described above can be used.

This time the calculation was done with a much more detailed hydrological model and the software product KAREN (Rauch & Kinzel 2007a). In reality 35 CSOs are located in Innsbruck, which means that there are 35 possible locations for overflow measurements. It is evident that it is neither possible nor reasonable to set up measurements on all sites. Therefore 14 CSOs were selected where water-level measurements could be used for calibration. The selection of measurement sites is based on prior simulations with an uncalibrated hydrodynamic model and on experience of the sewer system operator to catch those CSOs with the highest annual overflow volume. This enables one to measure the number of overflows in a very exact way and the overflow volume using further calculation methods from simple overflow equations to more complex CFD simulations. The results of CFD simulation to gain water-level/overflow relationships are shown in (Fach et al. 2008).

A rather complex hydrological model was built containing all 35 CSOs and further 11 CSOs in surrounding municipalities. Figure 4 shows the hydrological model of Innsbruck in KAREN. For calibration and validation data from 30\% of all CSOs was available for a period of approximately two years (1st January 2006–22nd October 2007).

Following (ÖWAV-RB 19, 2007) a simulation over a 10-year period is required to calculate CSO efficiency. Generally, the essential high-resolution rainfall data is available from the Austrian rainfall database NIEDA (Rauch & Kinzel 2007b). Because the rainfall series provided end before the start of the measurement campaigns, rainfall data measured simultaneously to the CSO measurements from three rain-gauges was used for calibration.

Figure 5a compares overflow volume simulated and measured of the entire system during the calibration period. Additionally, the deviation for each CSO is shown which reaches from \( -6.6\% \) to \( +2.9\% \). As the sum of the overflow volume highly varies among the different sites the values are presented on a logarithmic scale. The real overflow volume
of the entire system is unknown, so the improvement of calibration due to an increasing number of calibration sites cannot be proofed. Instead Figure 5b shows how the deviation of overflow volume simulated and measured at the 14 CSOs measured decreases with raising number of calibration sites.

Each catchment was calibrated individually. The calibration parameters are the effective impervious area, the time of concentration on the surface, the flow time in the sewers, the storage volume activated in the sewers (as annual average) and the interceptor capacity downstream. Table 2 shows how the total effective impervious area and the total storage volume activated in the sewers were adapted during calibration process.

**CONCLUSIONS**

When collecting data needed for the calibration of a hydrological sewer model it is crucial to pay attention to the selection of measurement sites and to the selection of rainfall events. To predict the total overflow volume selecting the relevant CSOs with the major contribution to total overflow volume is better than choosing those CSOs with the major contribution to impervious catchment area allocated.

Although long-term calibration is preferred to calibration on single events, single events can be used when increasing the number of measurement sites to reach a similar accuracy. The selection of rainfall events plays a decisive role. While a maximum deviation of less than 15% could be reached when calibrating on the five rainfall events with highest peak or on the five rainfall events with the longest duration a pure random selection can result in a complete false estimation of overflow volume with a deviation of more than 75%.

Although all the results shown are case specific and any additional sources of uncertainties (e.g. measurement uncertainties, spatial rainfall distribution) were disregarded, this investigation gives an idea of relevant considerations when arranging measurement campaigns.

The application of the methodology described in this paper on the sewer system of Innsbruck shows how those considerations can be implemented. In this case it was
possible to calibrate a hydrological model sufficiently when calibrating on 30% of all existing CSOs.

Further studies are needed to analyze more calibration parameters like CSO effluent or the runoff to the waste water treatment plant including not only values biased but also hydrographs. Additionally, model-independent strategies for selecting relevant measurement sites have to be analyzed. As the selection of rainfall events for calibration is a crucial step in calibration process this also needs to be examined in detail.

REFERENCES


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