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System-Wide Real Time Control Strategies for Overflow Volume Reduction - Extrapolating Annual Performance Indicators

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Abstract: Advanced real time control strategies of sewer networks can provide a significant contribution to the reduction of overflow volumes. Before full-scale implementation, these strategies need to be tested over long-time periods to calculate key performance indicators, such as yearly reduction in overflow volumes. This evaluation is often hindered by lack of sufficiently long data series. A new method was proposed to extrapolate yearly CSO reduction performance by using simulations of a limited number of CSO events. This article evaluates the precision of this extrapolation method by testing its precision in estimating CSO volumes yearly reduction for a synthetic example and a case study in Copenhagen (Denmark). The results showed a minor difference (2-3%) in the estimated CSO reduction for the synthetic example. However, the method overestimated the yearly CSO reduction for the real case study, mainly due to yearly variation and to non-linearity in the performance of control strategies. These preliminary results suggested that the extrapolation method converges with a lower number of CSO events compared to a simple sum of CSO volumes. Both the methods are thus suggested to obtain a more precise estimation of the yearly performance of advanced real time control strategies.

Keywords: Real Time Control, Model Predictive Control, Key Performance Indicators

1. INTRODUCTION

The digital transformation of the water sector is creating great opportunities for the implementation of new online control strategies, which ranges from local controls to system-wide optimization strategies (García et al., 2015; Lund et al., in press). System-wide Real Time Control (RTC) and Model-Predictive-Control (MPC) strategies, have been implemented at full scale (Mollerup et al., 2017) and in few cases a long-term evaluation of their environmental benefits is available (Fradet et al., 2011). Model-based evaluation of control strategies is therefore required by existing guidelines for control implementation (see for the example the German M180 guidelines - Schutze et al., 2008).

Given the highly spatial and temporal variability of rainfall, performance assessment of control strategies requires long-term simulations, i.e. the evaluation cannot be limited to few event in order to fully represent inter-event variability. Also, performance indicators are often expressed on a yearly basis (e.g. yearly reduction in Combined Sewer Overflows (CSO) volume), rather than on an event basis.

Van Daal et al. (2017) presented a comprehensive framework for model-based assessment of RTC strategies. However, the proposed framework relies on extensive measurements which are difficult to obtain for complex full-scale systems. Lack of data is exacerbated when looking at MPC strategies, which also requires rainfall forecast data. Löwe et al. (2016), for example, starting from a total of 422 rains events, identified 130 CSO events, where only 98 were included in the control evaluation due to issues in the dataset.

Excessive simulation time is also a recognized issue that limits the number of simulated events. For example, Meneses et al. (2018) used a detailed hydrodynamic model to evaluate a MPC strategy and limited their analysis to 46 selected events over a 5-year period. In order to extrapolate long-term (yearly) performance indicators based on a limited number of simulations, Meneses et al. (2018) applied a method originally applied for estimation of Expected Annual Damages in urban flood risk assessment (Zhou et al., 2012; Olsen et al., 2015). This article aims at assessing the applicability of this method for evaluating RTC and MPC strategies (based on CSO volume reduction). Firstly, the extrapolation method is tested on a synthetic example. Results from the system presented in Löwe et al. (2016) are then used to assess the validity of the proposed method.

2. MATERIALS AND METHODS

2.1 Extrapolation method

The proposed extrapolation method relies on the calculation of a *CSO density curve* f_{CSO} (Figure 1), which is calculated by dividing the CSO volume for each event (V_{CSO}) by its return period. The CSO volume can either be defined for a single discharge point or as a sum of discharges across a defined catchment. The return period should be based on the CSO frequency, but this requires the availability of long time series of overflow events. Since this is rarely available, the rainfall return period can also be used (as in Meneses et al., 2018). However, it should be underlined that the non-linear nature of overflow events does not necessarily ensure a direct relationship between rainfall and CSO frequency.

After calculating f_{CSO} for different scenarios (baseline and control strategy), the relative reduction in yearly CSO volume (*ΔCSO*) can be estimated as:

$$\Delta\mathrm{CSO} = 1 - \frac{\int f_{\mathrm{CSO,RTC}}(u)\,\mathrm{d}u}{\int f_{\mathrm{CSO,baseline}}(u)\mathrm{d}u} \tag{1}$$

where $f_{\mathrm{CSO,baseline}}(u)$ [m^3/year] is the CSO density curve for the baseline scenario; $f_{\mathrm{CSO,RTC}}(u)$ [m^3/year] is the CSO density curve for the control scenario, and u is the logarithm of the return period.

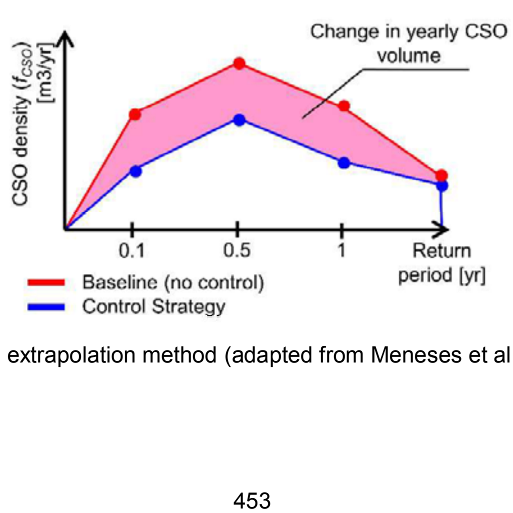

Figure 1. Schematization of the extrapolation method (adapted from Meneses et al., 2018)).

2.2 Case Studies

Synthetic Example. A total of 1,000 CSO volumes for the baseline scenario ($V_{CSO,baseline}$) were generated by sampling from a lognormal distribution (Figure 2 - left) and then randomly subdivided into 10 different years (i.e. there were 100 events for each year). The CSO volume for the control scenario ($V_{CSO,RTC}$) was then calculated by assuming a non-linear relationship, defined based on the pattern observed in real case studies (Löwe et al., 2016; Meneses et al., 2018). According to this pattern, control is able to avoid all small events (reduction close to 100%), while it does not have a significant reduction effect on big events (i.e. where the magnitude of the event is bigger than the system storage capacity).

Lynetten integrated MPC. Simulated CSO volumes from the Lynetten catchment, located in the city centre of Copenhagen (Denmark) were used. The sum of discharges from 9 CSO structures was used to evaluate the control performance. The CSO volumes were simulated by using rainfall data from the period 2000-2013. These rain data resulted in 921 CSO events over 13 years (ranging from a minimum of 54 to a maximum of 84 CSO events per year). The integrated MPC strategy described in Löwe et al. (2016) was applied to the catchment, resulting in the CSO volumes shown in Figure 2 (right). It should be noted that for few events the control strategy resulted in an increased CSO volume compared to the original discharges.

2.3 Comparison Methodology

For each case study the following steps were followed:

(a) yearly CSO reduction is calculated by using the whole available dataset (“true” CSO reduction);

(b) a subsample of CSO events is selected from a specific year (representing the situation where only limited event time series are available). The yearly reduction in CSO is extrapolated according to the methodology described in 2.1;

(c) step (b) is repeated with an increasing size of the subsample;

(d) the extrapolated CSO reduction is compared against the value obtained by using a simple sum of CSO volumes.

Points (b-d) were repeated 100 times in order to get a better overview of the precision and accuracy of the proposed methodology.

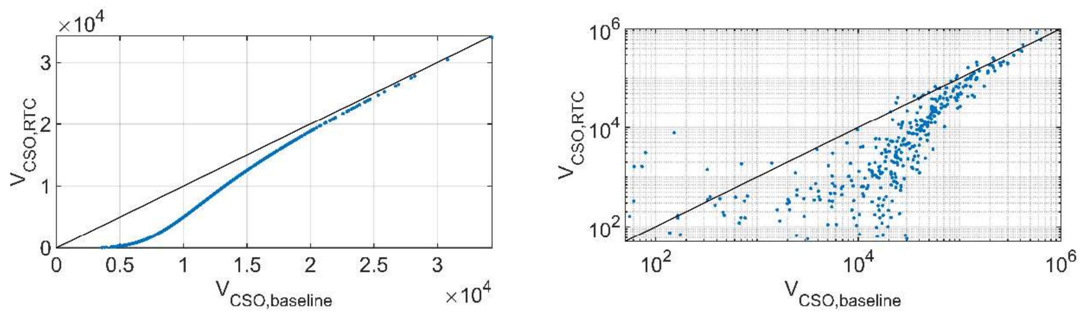

Figure 2. Comparison between CSO volumes without control (x-axis) and with control (y-axis) for all the analysed events. (left) Synthetic example. (right) Results for an integrated MPC strategy in the Lynetten catchment.

3. RESULTS AND DISCUSSION

Synthetic Example. Figure 3 shows how the extrapolation method quickly converged to a CSO reduction with a limited subsample of CSO events (10-15). The traditional method, based on the simple sum of volumes, showed a lower accuracy and tended to a greater underestimation of the removal potential. Overall, the extrapolation method resulted in a slight overestimation of the yearly CSO reduction ("true" 38% - simulated 39%).

Lynetten integrated MPC. Figure 4 highlights the high variability in CSO volumes for the different years, resulting in different yearly reductions (ranging from a minimum of 11% to a maximum of 64%, with an average over the 13 year of 41%).

The tendency to overestimate CSO reduction shown in the synthetic example was exacerbated for this case. This bias is mostly due to the assumption in a monotone, linear relationship between CSO volume and its reduction. Since the control performance are not linearly proportional to the event magnitude (e.g. in the case of coupled rain events), the integral of the function $f_{\mathrm{CSO,RTC}}$.is not monotone. Since the term $\int\ f_{\mathrm{CSO,RTC}}\,(u)\,\mathrm{d}u$ was calculated by using a trapezoidal integration rule

Nevertheless, the extrapolation method seems to converge to the final value more rapidly compared to simple arithmetic sum of CSO volumes. Also, the extrapolation method is less sensitive to the bias due to subsamples taken in years that are characterized by lower performance compared to the average value. For example, the control performance for 2007 and 2010 (Figure 4*)* were quite low (12.5% and 11.5%, respectively, against the 41% average), since these years where characterized by low-return period events. Nevertheless, the extrapolation method suggested an overall removal performance of around 20-30% (2007 data) and 40-30% (2010 data).

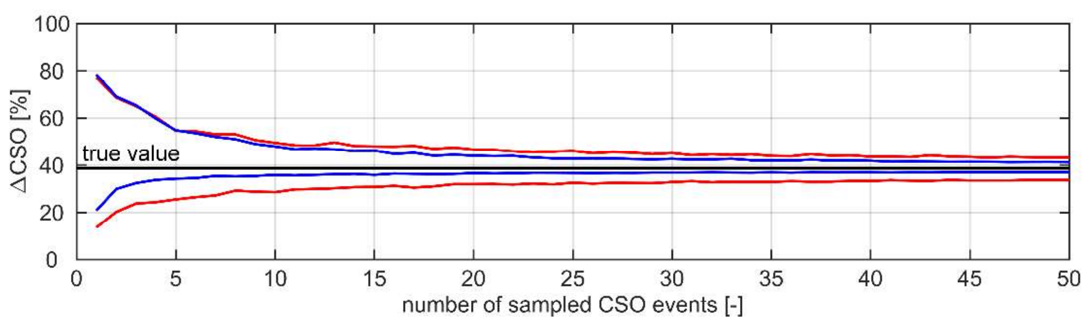

Figure 3. Estimated yearly reduction in CSO volume for the synthetic example by using the simple sum of CSO volumes (red) and the extrapolation method (blue) as function of number of sampled events. The lines shows the 5-95 percentiles for the 100 realizations.

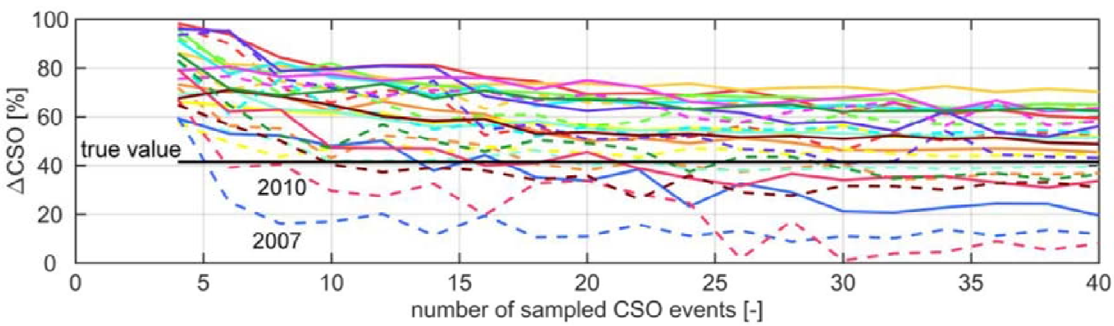

Figure 4. Estimated yearly reduction in CSO volume for the Lynetten example by using the simple sum of CSO volumes (dashed line) and the extrapolation method (solid line) as function of analysed events. Different years are visualized by using different colours. Lines shows the median value for the 100 realizations.

CONCLUSIONS

This preliminary assessment of the performance extrapolation method showed promising results in terms of convergence to the yearly performance indicator. However, the observed bias in CSO reduction, highlighted the need for further developments for accounting in the non-linearity of performance of RTC-MPC strategies. Also, further estimation of the method's accuracy compared to the simple sum of volumes is needed.

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