Probabilistic runoff volume forecasting in risk-based optimization for RTC of urban drainage systems

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A B S T R A C T
This article demonstrates the incorporation of stochastic grey-box models for urban runoff forecasting into a full-scale, system-wide control setup where setpoints are dynamically optimized considering forecast uncertainty and sensitivity of overflow locations in order to reduce combined sewer overflow risk. The stochastic control framework and the performance of the runoff forecasting models are tested in a case study in Copenhagen (76 km² with 6 sub-catchments and 7 control points) using 2-h radar rainfall forecasts and inlet flows to control points computed from a variety of noisy/oscillating in-sewer measurements. Radar rainfall forecasts as model inputs yield considerably lower runoff forecast skills than “perfect” gauge-based rainfall observations (ex-post hindcasting). Nevertheless, the stochastic grey-box models clearly outperform benchmark forecast models based on exponential smoothing. Simulations demonstrate notable improvements of the control efficiency when considering forecast information and additionally when considering forecast uncertainty, compared with optimization based on current basin fillings only.

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1. Introduction
This article investigates the application of probabilistic multi-step runoff forecasts generated by simple, conceptual stochastic models (in the form of so-called stochastic grey-box models) in system-wide, forecast-based optimization for real-time control (RTC) of urban drainage networks. A drainage network is considered to be controlled in real time if process variables are monitored in the system and used to operate actuators affecting the flow process (Schütze et al., 2004). RTC is an efficient tool for responding to changing demands that are defined for urban drainage systems (Rauch et al., 2005; Vanrolleghem et al., 2005) and is increasingly applied to operate these infrastructures in an efficient manner (for example, Mollerup et al., 2013; Nielsen et al., 2010; Pabst et al., 2011; Pleau et al., 2005; Puig et al., 2009 and Seggelke et al., 2013). In particular, RTC can support the operation of combined sewer systems, which are used in most of the larger European cities and are constantly challenged by increased impervious area and changing rainfall patterns (Arnbjerg-Nielsen et al., 2013; Willems et al., 2012).

Most RTC implementations aim to minimize the volume of combined sewer overflows (CSO). This is achieved by dynamically controlling flows in the system to achieve an optimal exploitation of the available storage volume, especially in cases with an uneven spatial rainfall distribution over the catchment. RTC is classically performed using static if-then-else rules (Seggelke et al., 2013; for example) that are optimized off-line based on heuristics and model simulations, but mathematical optimization routines are also applied (Pleau et al., 2005, Puig et al., 2009). Clearly, information on the future evolution of the urban drainage system (i.e., the runoff expected in the near future) should contribute to a more efficient optimization of the controlled...
system. Significant developments have been made in the last decade in terms of radar-based rainfall forecasting (Krämer et al., 2005, 2007; Thordahl et al., 2014; Vieux and Vieux, 2005) and radar-based urban runoff forecasting (Achleitner et al., 2009; Löwe et al., 2014a; Schellart et al., 2014; Thordahl and Rasmussen, 2013), paving the way for the application of radar-based online runoff forecasts in RTC.

However, multiple sources of uncertainty affect the runoff forecasts generated by models (see the discussions in Deletic et al. (2012), Schilling and Fuchs (1986) and Sun and Bertrand-Krajewski (2013)): input uncertainty, model structure uncertainty, parameter uncertainty and measurement uncertainty (e.g., level and flow). The examples in Schilling and Fuchs (1986), Schilling (1991) and Schellart et al. (2011) demonstrate that uncertainty of the measured and forecasted rainfall input is often the major factor affecting the online performance of runoff forecast models. Previous studies have evaluated the accuracy of online runoff forecasts based on radar rainfall input in an urban setting and found the forecast performance diminished for lead-times greater than 90 min (Achleitner et al., 2009) and between 60 and 120 min (Thordahl and Rasmussen, 2013).

Considering the large uncertainties of urban runoff forecasts, it has been hypothesized that the uncertainties may adversely impact the efficiency of forecast-based RTC schemes (Breinholt et al., 2008; Schütze et al., 2004). As a result, RTC algorithms that account for these uncertainties in mathematical optimization have recently emerged. Examples include the tree-based control algorithm, which was proposed for control of (non-urban) drainage water systems by Maestre et al. (2013), and the dynamic overflow risk assessment (DORA; Vezzaro and Grum, 2014) for urban drainage systems that performs a system-wide optimization based on the computed risk of overflow.

Accounting for the uncertainty of runoff forecasts in RTC requires that an estimate of this uncertainty is provided as an input to the control algorithm. The literature on uncertainty quantification in rainfall runoff modelling is abundant. Informal approaches (GLUE) are popular in urban hydrology (e.g., Dotto et al., 2012; Freni et al., 2009; Vezzaro and Mikkelsen, 2012), while more formal Bayesian approaches without (Del Giudice et al., 2015a; Kavetski et al., 2006) and with data assimilation routines (Moradkhani et al., 2012; Vrugt et al., 2013) were developed mostly for natural catchment hydrology. Model estimation and updating in these approaches are commonly based on Monte Carlo simulations, and they can therefore be difficult to apply in an online context (Del Giudice et al., 2015b).

Recent research in the Storm- and Wastewater Informatics Project (SWI, 2015) has therefore focused on the application of so-called stochastic grey-box models for probabilistic online runoff forecasting over multiple prediction horizons. This type of model combines a simple and fast stochastic model structure with a data assimilation routine in the form of an extended Kalman filter, allowing the user to generate probabilistic forecasts with time-dynamic uncertainty quantification. The application of such models in urban hydrology was first tested by Carstensen et al. (1998) and Bechmann et al. (1999). Breinholt et al. (2011, 2012) developed rainfall-runoff model structures, and the performance of these for probabilistic flow predictions was assessed by Thordarson et al. (2012). Finally, Löwe et al. (2014a) analysed the influence of different rainfall inputs on runoff forecast performance, while different options for parameter estimation were compared in Löwe et al. (2014b).

The work presented here combines these recent developments: probabilistic, radar-rainfall based runoff forecasts from stochastic grey-box models have been combined with a risk-based optimization algorithm that accounts for time-dynamic forecast uncertainty (DORA, Vezzaro and Grum, 2014) and integrated into a full-scale, system-wide RTC setup, providing a proof of concept for the case of applying stochastic forecasts in RTC. The setup is tested in a case study with noisy real-world measurements and six sub-catchments with distinctly different characteristics. The purpose of this article is to:

- demonstrate this new, stochastic, system-wide real-time control setup for urban drainage systems,
- evaluate how the consideration of runoff forecast uncertainty influences the efficiency of the RTC scheme, and
- evaluate what runoff forecast performance and what control efficiency can be obtained with stochastic grey-box models and radar rainfall input under realistic conditions in a variety of catchments.

The new control setup applies stochastic grey-box models for runoff forecasting. However, other probabilistic forecasting methods (such as the ones presented by Todini (2008), Van Steenbergen et al. (2012), Vrugt et al. (2005) or Weerts et al. (2011)) could easily be implemented. Thus, the proposed framework is generic in this respect.

2. Methods

2.1. Stochastic real-time control setup

2.1.1. General setup

A system-wide control setup was applied. Control points need to be defined by the users and are typically located at major actuators, such as the outlet of storage basins or pumping stations. Runoff forecasts were generated by a separate stochastic model (Section 2.1.2) for the inflow to each control point. Based on the inflow forecasts and online observations of the current basin fillings, the DORA algorithm was then used to optimize the outflow from all of the control points, aiming to minimize the overall overflow risk in the catchment (Section 2.1.3). A control time step of 2 min was applied and a maximum forecast horizon of 2 h was considered. Correspondingly, new runoff forecasts were generated every 2 min for 2 h into the future with a resolution of 60 time steps (intervals of 2 min).

The online operation of the framework is illustrated in Fig. 1. It can be split into 5 steps that are executed every 2 min:

1. Data collection – the runoff forecast models apply rainfall forecasts as an input and flow observations for updating the model states. In addition, the current basin filling is required as an input to the control algorithm. Depending on the source, these data are either downloaded as text files through FTP connections or directly imported from the SCADA system through the standard OPC UA (Unified Architecture) protocol (Mahinke et al., 2009).

2. Pre-processing – flow observations are required to update the states of the runoff forecast models (Section 2.1.2). However, for many control points, no direct inflow measurements are available. Instead, these need to be constructed by “software sensors” from a combination of indirect measurements (such as level in and outflow from a storage basin). Catchment specific pre-processing routines (see Appendix A) are therefore implemented in this module. The software WaterAspects (Grum et al., 2004) was applied for this step in our work, while future implementations will apply JEP and R scripts.

3. Runoff forecasting – a separate stochastic grey-box model (Section 2.1.2) is applied for forecasting the inflow volume to each control point. The model output is a distribution of
forecasted runoff volume for each considered horizon, discretized in 50 quantiles from 1 to 99%. Each model in our work was implemented as an executable (FORTRAN-based) that communicates with the control server via text files. An R-based setup that directly communicates with the database is currently being implemented.

4. Identifying set points for the actuators using the DORA algorithm (Section 2.1.3) – this module is implemented in JAVA. The overflow risk for each control point is computed based on the current basin filling and the forecasted distribution of runoff volumes in the form of quantiles.

5. The new outflow set points for the actuators are sent to the SCADA system through the standard OPC UA protocol.

A control software is required to manage the execution of the tasks mentioned above, the communication with external data sources and actuators, data storage in a database and quality control of measurements and simulation results. In our case, the STAR® Utility Solutions™ framework (Nielsen and Ønnerth, 1995) was used. The framework is implemented in JAVA but allows for the execution of external programs written in, for example, R. The framework can be installed either on a dedicated control server, on a cloud server or within the end-user’s own virtual server environment.

2.1.2. Runoff forecasting using stochastic grey-box models

2.1.2.1. Model structure. A simple cascade of three linear reservoirs was applied for forecasting runoff volume in the inflow to a single control point. We did not consider more elaborated model structures as the purpose of this article is to provide a proof of concept. The model was set up as a stochastic grey-box model in a state-space layout as described by Breinholt et al. (2011) and shown in state Eq. (1), which are implemented using stochastic differential equations (SDEs) and observation Eq. (2). The setup includes an extended Kalman filter, which updates the model states whenever new flow observations become available (Kristensen et al., 2004). The model was implemented in the open source software CTSM-R (Juhl et al., 2013).

\[ \begin{bmatrix} dS_{1,t} \\ S_{2,t} \\ S_{3,t} \\ a_0 \end{bmatrix} = \begin{bmatrix} A \cdot I + a_0 - \frac{1}{K} S_{1,t} \\ \frac{1}{K} S_{1,t} - \frac{1}{K} S_{2,t} \\ \frac{1}{K} S_{2,t} - \frac{1}{K} S_{3,t} \\ 0 \end{bmatrix} + \begin{bmatrix} \sigma_1 S_{1,t} \\ \sigma_2 S_{2,t} \\ \sigma_3 S_{3,t} \\ \sigma_4 \cdot I \end{bmatrix} d\omega_t \] (1)
\[ Y_k = \frac{1}{R} S_{3,k} + D_k + e_k \]  

(2)

\[ S_1, S_2 \text{ and } S_3 \text{ correspond to the storage states, } A \text{ to the effective catchment area, } P \text{ to the rain intensity, } a_0 \text{ to the mean dry weather flow and } K \text{ to the travel time constant. The uncertainty of model predictions is described in the so-called diffusion term, which is driven by a vector Wiener process } d_{\chi(t)} \text{ (Iacus, 2008). Considering a time step } \Delta t, \text{ an increment } d_{\chi(t)} \text{ of this process is Gaussian with mean } 0 \text{ and covariance } \text{diag}(\Delta t, \Delta t, \Delta t, \Delta t). \]

The parameters \( \sigma_t \) scale the standard deviation of the diffusion process, which here increases linearly with the state value \( S_i \). We have included the mean dry weather flow \( a_0 \) as a state to allow the model to adapt to varying dry weather flows, which we have observed in some of the catchments considered in our case study. The index \( I = 1 \) during the updating step of the extended Kalman filter and 0 when generating runoff forecasts. The last-known estimate of \( a_0 \) was thus applied during the generation of multistep runoff forecasts.

The observation Eq. (2) relates time-continuous model predictions and flow observations \( Y_k \) at discrete time steps \( k \). This equation additionally includes a trigonometric function \( D \) to describe the variation of dry-weather flows (Breinholt et al., 2011) and the observation error \( e_k \) with standard deviation \( \sigma_e \).

A Lamperti transformation (Iacus, 2008) was applied to the state Eq. (1) to remove the dependency of the noise description on the state (Breinholt et al., 2011), as state-dependent SDEs are difficult to simulate numerically (Iacus, 2008).

The diffusion term in Eq. (1) accounts for the combined effects of input and model structure uncertainty. The observation error \( e_k \) in Eq. (2) can account for deficiencies in the sensor measurements as well as for oscillations resulting, for example, from varying pumping discharges. The latter were treated as noise if they occurred on short time scales of only few minutes, as such variations have only little effect on the basin volumes at the control points. The parameters \( A \) and \( K \), the uncertainty scalings \( \sigma_t \) of the diffusion term and the standard deviation of the observation error \( \sigma_e \) were estimated as part of the automated calibration routine.

2.1.2.2. Parameter estimation. The model parameters were determined in an automated calibration routine. As an objective function, we minimized the multistep probabilistic flow forecast error as described by Löwe et al. (2014b). Using the state prediction equations of the extended Kalman filter (Eqs. (17) and (18) in Kristensen et al. (2004)) and subsequently inserting the state predictions into the output prediction equations (Eqs. (11) and (12) in Kristensen et al. (2004)), a multistep flow forecast was generated at each time step \( k \) for forecast horizons \( i = 1 \ldots 60 \) with a resolution of \( \Delta t = 2 \text{ min} \). The forecasts were assumed Gaussian with mean \( \hat{Y}_{k+i|k} \) and forecast covariance \( R_{k+i|k} \). As an estimate for the probabilistic forecast error, we computed the continuous ranked probability score \( \text{CRPS}_{i} \) (Gneiting and Raftery, 2007) for each forecast horizon \( i \) as

\[ \text{CRPS}_{i} = \frac{1}{60-i+1} \sum_{i=1}^{60} \left( \text{CRPS}_{i} \right) \]

\[ = \int_{-\infty}^{\infty} \left( \hat{Y}_{k+i|k}(s) - H(s > Y_{k+i|k}) \right)^2 ds. \]  

(3)

where \( \hat{Y}_{k+i|k}(s) \) is the cumulative normal distribution function of the forecast flow, \( Y_{k+i|k} \) is the observed flow for the corresponding time step and \( H \) is the Heaviside function that takes the value 0 if \( s < Y_{k+i|k} \) and 1 otherwise. A closed-form solution of the CRPS is available for Gaussian \( P_{k+i|k}(s) \). However, we chose to evaluate the integral in Eq. (3) numerically for quantiles from 1 to 99% in steps of 2% to make the approach flexible for other distributional assumptions. A measure of average performance over all forecast horizons was defined as

\[ \text{CRPS}_{i} = \frac{1}{60-i+1} \sum_{i=1}^{60} \left( \text{CRPS}_{i} \right) \]

(4)

The RTC scheme requires forecasts of runoff volume as an input (see Section 2.1.3). Therefore, more weight is put on flow forecasts for shorter forecast horizons in Eq. (4). These have a stronger influence on forecasts of runoff volume, which are generated as an integral over flow forecasts for several horizons. Finally, averaging the \( \text{CRPS}_{i} \) over all time steps \( k \) provided the objective function for parameter estimation, which we aimed to minimize.

We applied the heuristic optimization algorithm described by Tolson and Shoemaker (2007) with 2500 objective function evaluations for automated parameter estimation. The dry weather flow variation \( D \) was fixed during the parameter estimation process. The corresponding parameters were estimated separately during a dry weather period.

2.1.2.3. On-line forecast generation. To generate probabilistic runoff forecasts online, we performed scenario simulations of the model Eq. (1), starting with the updated states provided by the extended Kalman filter at time step \( t \) and ending at the maximum considered forecast horizon \( t + j \). We considered \( N = 1000 \) scenarios. The forecasted flow for each scenario was integrated into a runoff volume. The resulting empirical distribution of forecasted runoff volumes served as input to the control algorithm in the form of quantiles with a resolution of 2%. The approach was described in more detail by Löwe (2014) and Löwe et al. (2014a).

The generation of on-line runoff forecasts was based on scenario simulations of the stochastic process without distributional assumption, while assumed-Gaussian forecasts were generated using the extended Kalman filter during parameter estimation. This inconsistency is a shortcoming of the current setup, which was caused by the need to generate forecasts with limited computational effort during parameter estimation.

2.1.3. Real-time control under uncertainty

We applied the dynamic overflow risk assessment (DORA, see Vezzaro and Grum (2014) and Vezzaro et al. (2014)) in this study. This approach, in the terminology of Mollerup et al. (2015), acts on the optimization layer of the real-time control setup, aiming for a system-wide (across the entire catchment) reduction of the risk of CSO using a forecast-based mathematical optimization routine that accounts for both forecast uncertainty and impact cost.

The overflow risk for each controlled point is calculated by:

1. Subtracting the basin outflow volume over the forecast horizon and the currently free basin volume from the forecasted probability distribution of runoff volume, and
2. Multiplying the resulting probability distribution of overflow by a constant CSO unit cost that is user-defined for each overflow location (which reflects the sensitivity of the different receiving waters). More sensitive control points (e.g., discharging to bathing areas) are given higher CSO unit costs than less sensitive control points (e.g., discharging close to the wastewater treatment plant (WWTP) inlet).

The motivation for DORA is that stochastic forecasts are needed because a deterministic forecast only leads to optimal control decisions if the loss function applied in optimization does not depend on the uncertainty range associated with the forecasted variable. Even for the simple CSO unit cost applied here, this is clearly not the case because the overflow risk is a discontinuous function that is
zero for small forecasted runoff volumes and increases linearly for larger forecasted runoff volumes that would lead to an overflow of the basin.

At each control time step (in this study set to 2 min, i.e., each time a new set of measurements from the catchment becomes available), DORA executes the following loop (Fig. 2):

- **Step 1:** The available storage volume for each basin is calculated using online measurements.
- **Step 2:** Runoff forecasts (and the associated uncertainty) are used to estimate the overflow risk for each controlled point. The probability density for the forecasted runoff volume is here described empirically by a set of quantiles provided by the stochastic grey-box model. This is different from the approach in Vezzaro and Grum (2014), who described forecast uncertainty analytically by a Gamma distribution with roughly fixed parameters.
- **Step 3:** A genetic algorithm (Meffer et al.) is used to identify the optimal set of flows between all of the basins in the catchment, minimizing the total CSO risk. The settings of the algorithm were defined for the study area after off-line tests, which focused on convergence (especially in dry weather conditions, when CSO risk is low and several solutions form a Pareto front). By initializing the algorithm from the solution obtained at the previous time step, a population size of 100 and a maximum of 50 evolutions were sufficient to obtain the desired convergence and reliability. When the CSO risk is low (e.g., after the end of a rain event with no new rainfall within the forecast horizon), DORA empties the controlled system as quickly as possible, with the highest priority on the control points with the largest CSO cost.
- **Step 4:** Optimal set points for each basin outflow are sent to the actuators in the system.

DORA does not currently account for transport times in the optimization step 3 (see Vezzaro and Grum (2014)). Instead, an immediate transfer of outflow volumes is assumed between the control points.

2.2. Performance evaluation

We validated the stochastic forecasting and control setup in a two-step procedure. First, we evaluated runoff forecasting performance by comparing forecasts and observations. Second, we determined the efficiency of the control setup with and without forecast uncertainty and considering different rainfall inputs.

2.2.1. Evaluation of forecast quality

In the evaluation of forecast performance, we focused solely on lead times of 120 min (60 time steps) into the future because this is the longest horizon considered in the system-wide control scheme and may be considered as the worst case.

2.2.1.1. Point forecast skill.

To assess point forecast quality, we applied a skill score defined as:

\[
SPI = 1 - \frac{\sum_{k=1}^{N} \left( \frac{V_{k+60|k,50\%} - \sum_{i=1}^{60} Y_{k+i} \cdot \Delta t}{\sum_{j=1}^{60} \left( (1 - \lambda) \cdot Y_{SM,k-1} + \lambda \cdot Y_{k} \right) \cdot \Delta t - \sum_{i=1}^{60} Y_{k+i} \cdot \Delta t} \right)^2}{\sum_{k=1}^{N} \left( \sum_{j=1}^{60} \left( (1 - \lambda) \cdot Y_{SM,k-1} + \lambda \cdot Y_{k} \right) \cdot \Delta t - \sum_{i=1}^{60} Y_{k+i} \cdot \Delta t \right)}
\]  

(5)

In Eq. (5), the numerator of the fraction is the mean squared error of the runoff volume forecasts generated by the stochastic grey-box models, \( V_{k+60|k,50\%} \) is the median of the probabilistic forecast of runoff volume generated by the stochastic grey-box models at time step \( k \) for a forecast horizon of 60 time steps. \( Y_{k} \) are the flow observations for the same period. These are available in intervals of \( \Delta t = 2 \) min and for a total of \( N \) time steps during an event for which the forecast skill is computed.

The denominator of the fraction in Eq. (5) is the mean squared error of a reference (or benchmark) forecast. As a reference, we considered locally constant runoff volume forecasts derived using exponential smoothing (Brown and Meyer, 1961). \( Y_{SM,k-1} \) is the smoothed flow observation obtained for the previous time step and \( \lambda \) is the smoothing parameter, which was tuned to minimize the 60 step forecast error shown in the denominator in Eq. (5) during the calibration events described in Section 3 and which can vary between 0 and 1.

We denote the resulting skill score as the smoothed persistence index (SPI) because it resembles the persistence index described in Bennett et al. (2013). However, a smoothed value is applied as the reference forecast instead of the last observation to make the score more robust towards the noisy flow measurements we
encountered in our study. Ideally, the SPI would take a value of 1 for a perfect runoff forecast. Values smaller than 0 indicate that the forecasts generated by the stochastic grey-box models have a bigger mean squared error than the locally constant forecast based on exponential smoothing.

2.2.1.2. Forecast reliability. In a probabilistic sense, it is desirable for the runoff forecasts to be reliable. An \( \alpha \% \) prediction interval should empirically include \( \alpha \% \) of the observations, i.e., have an observed coverage rate of \( \alpha \% \). This property of the probabilistic forecasts can be assessed by plotting predicted (or nominal) and observed coverage rates against each other in reliability diagrams (Murphy and Winkler, 1977). Such diagrams are easier to understand and simplify communication with practitioners and were therefore preferred over the probability integral transform used by, for example, Hemri et al. (2013) and Renard et al. (2010). Ideally, predicted and observed coverage rates should be equal. Predicted coverage rates smaller than the observed coverage rates indicate an overestimation of forecast uncertainty by the model, while the reverse indicates an underestimation of forecast uncertainty.

2.2.1.3. Sharpness of forecasts. Finally, given a reliable probabilistic forecast, it is desirable for it to be as sharp (or “narrow”) as possible. A common measure is the sharpness or average width of an \( \alpha \% \) prediction interval. Jin et al. (2010) normalized this measure with the observation to obtain the average interval width \( \text{ARIL} \). The observation, however, is not related to the forecast and \( \text{ARIL} \) will be difficult to evaluate if the observations approach zero, for example. We therefore applied a modified version of \( \text{ARIL} \) in which we normalized by the absolute value of the forecast median. We applied this version for the 90\% prediction interval as a measure of forecast uncertainty:

\[
\text{ARIL}^* = \frac{1}{N} \sum_{k=1}^{N} \left( \frac{\hat{V}_{95\% k+60k} - \hat{V}_{5\% k+60k}}{\hat{V}_{50\% k+60k}} \right) \tag{6}
\]

In (6), \( \hat{V}_{95\% k+60k} \), \( \hat{V}_{5\% k+60k} \), and \( \hat{V}_{50\% k+60k} \) correspond to the 95\%, 5\%, and 50\% quantiles of the probabilistic runoff volume forecasts generated at time step \( k \) for a lead time of 120 min (60 time steps). Smaller values of \( \text{ARIL}^* \) indicate narrower prediction intervals.

2.2.2. Evaluation of control efficiency

To evaluate the effect of different forecast inputs on the efficiency of the system-wide control algorithm, simulations need to be performed in a model that describes flows in all relevant parts of the catchment, includes all actuators and allows for the evaluation of CSO in different scenarios (as demonstrated by Seggelke et al., 2013; for example). In the evaluation, this model (Section 3.2) replaces the actuators in Fig. 1 and provides current basin fillings as input to the DORA algorithm.

To compare the performance of the setup in different scenarios, we focused on the evaluation of overflow volumes and cost accumulated over a number of rain events. Reduced overflow volumes in a scenario indicate an improved performance of the control system. The best performing setup minimizes the total overflow cost, which corresponds to the overflow volume weighted according to the expected environmental impact at the location of the overflow structures. The weighting factors correspond to the CSO unit cost defined in DORA for the different overflow structures (see Section 2.1.3 and Table 1 in Section 3).

2.2.3. Considered scenarios

Five scenarios were simulated to (i) evaluate the influence of runoff forecast uncertainty on the efficiency of system-wide control and (ii) estimate what forecast performance and what control efficiency can be achieved under realistic conditions:

1. **AU** – Rain gauge based runoff forecast with uncertainty: The inputs for the stochastic grey-box models were the rain gauge measurements averaged for each sub-catchment (see Section 3.3.1). Rainfall forecasts are required as model input for the generation of runoff forecasts. In this scenario, perfect rainfall forecasts derived from the rain gauge measurements for the forecast period where applied, both when calibrating the parameters of the runoff forecast models and when evaluating runoff forecasting performance and control efficiency.

2. **ANU** – Rain gauge based runoff forecast without uncertainty: Runoff forecasts were generated in the exact same way as in scenario AU. However, runoff forecast uncertainty was neglected when evaluating control performance by defining a forecast distribution with negligible standard deviation (the forecast median divided by 2500) around the forecast median.

3. **BU** – Radar based runoff forecast with uncertainty: Radar rainfall measurements and forecasts (see Section 3.3.1) were used as model input for calibrating the runoff forecast models.

<table>
<thead>
<tr>
<th>Sub-catchment</th>
<th>Imper-vious area [ha]</th>
<th>Storage available for RTC [m³]</th>
<th>Max outflow [m³/s]</th>
<th>CSO unit cost [€/m³]</th>
<th>Controlled by DORA</th>
<th>Typology</th>
</tr>
</thead>
<tbody>
<tr>
<td>Colosseum (COL)</td>
<td>211</td>
<td>30,914</td>
<td>0.9</td>
<td>5</td>
<td>X</td>
<td>basin, pumped outflow, storage pipes, pumped outflow</td>
</tr>
<tr>
<td>East Amager (EAM)</td>
<td>228</td>
<td>44,425</td>
<td>2.1</td>
<td>25</td>
<td>X</td>
<td>storage pipes</td>
</tr>
<tr>
<td>Kloevermarken (KLO)</td>
<td>777</td>
<td>27,500</td>
<td>7.5</td>
<td>5</td>
<td>X</td>
<td>pumping station with storage in upstream pipe network</td>
</tr>
<tr>
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<td>733</td>
<td>27,000</td>
<td>1.1</td>
<td>25</td>
<td></td>
<td>storage pipe with gate</td>
</tr>
<tr>
<td>Lynetten WWTP (LYN)</td>
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<td>76</td>
<td>5 (6.4 wet weather mode)</td>
<td>1</td>
<td></td>
<td>CSO at WWTP inlet</td>
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<tr>
<td>St. Anne (SKT)</td>
<td>77</td>
<td>7987</td>
<td>1.3</td>
<td>5</td>
<td></td>
<td>basin, pumped outflow</td>
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<tr>
<td>Strandvaenget Basin (STB)</td>
<td>92</td>
<td>1020</td>
<td>3.9</td>
<td>25</td>
<td>X</td>
<td>CSO structure, pumped outflow</td>
</tr>
<tr>
<td>Pumping station (STP)</td>
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<td>2.4</td>
<td>1</td>
<td>X</td>
<td>pumping station</td>
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<tr>
<td>West Amager (WAM)</td>
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<td>13,490</td>
<td>1.0</td>
<td>5</td>
<td>X</td>
<td>basin, pumped outflow</td>
</tr>
<tr>
<td>Total</td>
<td>2279</td>
<td>153,312</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
for evaluating runoff forecasting performance and for evaluating control efficiency.

4. **BNU – Radar based runoff forecast without uncertainty:** Runoff forecasts were generated in the exact same way as in scenario BU. However, runoff forecast uncertainty was neglected when evaluating control performance by defining a forecast distribution with negligible standard deviation (the forecast median divided by 2500) around the forecast median.

5. **REF – No forecast:** This is a reference scenario for the evaluation of control efficiency only. In this scenario, DORA was used with a zero forecast as described by Vezzaro and Grum (2014). The control algorithm in this case simply attempts to equalize the basin fillings in the different sub-catchments, weighted according to the CSO unit cost at the overflow points (Table 1).

Scenario AU provides a base case with near-perfect rainfall forecast. Scenario BU, on the other hand, illustrates the runoff forecast quality and control efficiency that can be achieved with more realistic rainfall forecasts. As the skill of radar rainfall forecasts strongly decreases with the forecast horizon (Achleitner et al., 2009; Thorndahl and Rasmussen, 2013), scenario BU would be expected to yield lower runoff forecasting skill and reduced control efficiency as a result of the larger uncertainty of the rainfall input applied in this case.

If the consideration of forecast uncertainty has a positive impact on the performance of system-wide control (as hypothesized by Vezzaro and Grum (2014) and Løwe et al. (2014b)), then scenarios AU and BU should yield better control results than their counterparts ANU and BNU.

Finally, the reference scenario REF provides a reasonable benchmark for the control performance obtained when applying DORA with and without runoff forecasts as input.

3. Case study

3.1. Catchment

The case study was designed to test the setup in a situation where the runoff forecast models need to cope with a variety of sub-catchments with different characteristics (Table 1), where realistic rainfall forecasts are applied (Section 3.3.1) and where runoff forecasts are far from perfect (Section 3.3.1 and Appendix C). We considered the catchment of the Lynetten wastewater treatment plant (WWTP), which covers the central area of Copenhagen (Denmark) and has a total area of approximately 76 km².

The system-wide control strategy for the Lynetten catchment considers seven sub-catchments and nine overflow struc
tures (see Fig. 3), discharging to recipients with different sensitivities to CSO. Large storage basins were implemented in the catchment over the past three decades as a result of efforts to minimize CSO and secure bathing water quality in the harbour. The total storage capacity is approximately 153,000 m³.

Separate stochastic grey-box models were implemented to forecast runoff volumes for the inflow to each control point. No runoff forecasts were generated for the sub-catchments discharging to the St. Anne basin (SKT) and to the WWTP inlet (LYN) due to the very poor quality of the available flow and water level observations. Only the current filling rate at these control points was included in the optimization strategy to calculate the system-wide CSO risk and no control decisions were determined for the corresponding actuators. The Strandvænget sub-catchment comprises two control points at the basin outlet (STB) and the pumping station (STP) to the WWTP. Runoff forecasts were only generated for the basin inflow because the pumping station only receives inflows from STB. The characteristics of the sub-catchments are summarized in Table 1.

3.2. Catchment simulation model for the evaluation of control efficiency

We used a conceptual model of the Lynetten catchment (implemented in WaterAspects – Grum et al., 2004) to evaluate the control efficiency. Following the procedure presented by Borsanyi et al. (2008), this model was calibrated against a detailed MIKE URBAN model of the catchment. A sketch of the model together with a comparison of simulated and observed inflows to the control points EAM, COL, KLO, LER, SKT and WAM is provided in Appendix C for all rain events.

The generation of runoff was described using the time area method, and a simple time delay was applied for routing in pipes. Local controls existing in the catchment (e.g., pumping based on filling degree in basins) were implemented in the model. They were overridden by the DORA set points when system-wide control strategies were simulated.

Rain gauge measurements averaged over each sub-catchment (see Section 3.3.1) were used as input for the catchment simulation model.

3.3. Data and simulation periods

3.3.1. Rain data and in-sewer observations

A time step of 2 min was adopted for all of the datasets in this work, corresponding to the control time step of the existing control setup. Data available at higher temporal resolution were averaged, while data with lower temporal resolution were assumed constant in between observations (“zero order hold”). Online measurements were available for the period from November 2011 until September 2014.

Rain measurements from 29 gauges in the area (Fig. 3) with a temporal resolution of 1 min were available from the network of the Danish Water Pollution Committee (SVK), which is operated by the Danish Meteorological Institute (Jørgensen et al., 1998). A time series of mean areal rainfall was determined for each of the sub-catchments shown in Fig. 3 using Thiessen polygons.

Rain radar measurements and forecasts were available from the C-band radar of the Danish Meteorological Institute in Stevns. The data had a resolution of 10 min in time and 2 × 2 km in space. The radar data were time-dynamically adjusted to rain-gauge data at every time step as described in Løwe et al. (2014a), Thorndahl et al. (2013) and Thorndahl and Rasmussen (2013). A mean areal rainfall series was calculated for each sub-catchment from the radar data by computing a weighted average of the rainfall measured in different pixels. The weighting factors for this process were determined from the intersecting area between a pixel and the corresponding sub-catchment.

Historical radar rainfall forecasts were made available for forecast horizons of 10, 20, 30, 60 and 90 min. We interpolated the forecasts for horizons of 40, 50, 70 and 80 min and assumed that the rainfall forecasts for the 100–120 min horizons were equal to the forecast for the 90 min horizon. This is a limitation in our work caused by the data that were made available to us. In reality, a radar-based flow forecasting setup would be expected to perform slightly better than presented here.

Various level and flow measurements from the sewer network were available for the considered period (see Appendix A). In most sub-catchments, no direct measurements of the inflow to the control point were provided. However, inflow measurements are required to update the stochastic runoff forecasting models (see Eq. (2)) and to evaluate forecast performance. They were computed from the available data using the water balance for each control
Fig. 3. Catchment of the Lynetten wastewater treatment plant (WWTP) with control points in the combined sewer system and their respective sub-catchments.
point and (in some cases) rating curves (see Appendix A). This approach led to noisy flow measurements (see Appendix C) and proved problematic in the LER and STB catchments, where negative measurements were obtained after rain events because the water balance was not closed in some situations. Such systematically negative data were excluded from the updating of the forecast models and from the evaluation of forecast performance.

3.3.2. Selection of rain events

Rain events were identified from the mean areal radar rainfall measurements for the six sub-catchments where stochastic runoff forecasting models were implemented. An event was considered to start when any of the mean areal rainfall series exceeded a threshold intensity of 0.2 mm/10 min. The event was considered to end when the mean areal rainfall series for all sub-catchments were below this threshold for a period of at least 10 h.

Based on these criteria, a total of 422 rain events were identified between Nov 2011 and Sep 2014. Many of these events were unlikely to cause CSO due to the small rainfall volumes involved. In addition, significant data gaps were observed for many events. The number of events under consideration was reduced in the three-stage procedure shown in Table 2. Appendix B lists all 130 rain events identified after the first two stages of data inspection, while Appendix C depicts the observed inflow to the control points for these events. Rain events that were identified as problematic during visual inspection were excluded from the evaluation of forecast performance in the corresponding catchment as well as from the evaluation of control efficiency. These events are marked in the table in Appendix B and with a grey background in Appendix C.

In total, between 114 and 127 rain events were considered for the evaluation of forecast performance in the different sub-catchments, and 98 events were considered for the evaluation of control efficiency. Four rain events were selected for estimating parameters of the forecast models. These were chosen to cover different rainfall characteristics (short, intense and localized storms as well as widespread, long lasting rainfall) in different seasons and are marked in Appendix B.

4. Results

4.1. Forecast performance

This section focuses on the evaluation of runoff forecast performance obtained for the stochastic grey-box models. As explained in Section 2.2.1, all of the results shown in the following were derived for forecasts of runoff volume for a forecast horizon of 120 min, corresponding to 60 control time steps.

Fig. 4 shows the point forecast skill SPI obtained in all of the catchments. Skill values larger than zero indicate that the stochastic grey-box models are likely to cause CSO due to the small rainfall volumes involved. In addition, significant data gaps were observed for many events. The number of events under consideration was reduced in the three-stage procedure shown in Table 2. Appendix B lists all 130 rain events identified after the first two stages of data inspection, while Appendix C depicts the observed inflow to the control points for these events. Rain events that were identified as problematic during visual inspection were excluded from the evaluation of forecast performance in the corresponding catchment as well as from the evaluation of control efficiency. These events are marked in the table in Appendix B and with a grey background in Appendix C.

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4.2. Efficiency of system-wide real-time control

The total overflow volumes and cost obtained for the considered scenarios are shown in Fig. 8. In the reference scenario REF, overflow occurred for 87 of the considered rain events, leading to a total overflow volume of 0.95 10^6 m^3 (Fig. 8, left) and 12.0 10^6 units of overflow cost (Fig. 8, right).

Including forecast information in the control scheme in all cases lead to a strong reduction of overflow volumes and cost. As expected, overflow volumes and cost were smallest for scenarios AU and ANU because the future rainfall was considered known during the generation of runoff forecasts. Control efficiency was reduced if radar rainfall measurements and forecasts were used as input to the stochastic runoff forecasting models (for example, scenario ANU yielded 15% lower overflow volume and 20% lower overflow cost than scenario BNU). Nevertheless, in scenarios BU and BNU, the amount of overflow was also greatly reduced compared to the reference scenario REF.

The results obtained by the system-wide control scheme improved further if the uncertainty of the runoff forecasts was accounted for. The total overflow cost (i.e., the objective function of the control scheme) and volume in scenario AU were reduced by 33% compared to scenario ANU (Fig. 8). In scenario BU, the total overflow volume was reduced only minimally compared to scenario BNU (Fig. 8). This result was caused by a strong increase in forecast uncertainty at control point KLO. As a result, the optimization routine frequently assigned high outflows to this control point (reducing overflow volumes almost to zero), while outflows from STP were frequently minimized (leading to a strong increase in...
of overflow volumes at this point). However, the total overflow cost in this scenario was reduced by 20% compared to scenario BNU, meaning that CSO were diverted from more to less sensitive recipients.

5. Discussion

5.1. Dependency of runoff forecast skill on catchment and rainfall input

On average, the stochastic grey-box models outperformed the exponential smoothing benchmark in all of the considered sub-catchments. However, the forecast skill varied strongly between catchments and rain events.

If future rainfall was assumed to be known (scenario AU), the highest forecast skill was obtained for the smaller catchments (EAM, COL, WAM — see Fig. 4), where a reservoir cascade could suitably describe the runoff processes. For the more complex catchments, forecasts could be improved if somewhat more complex model structures were considered (Del Giudice et al., 2015a; Löwe et al., 2014a). However, simple models are desirable for online purposes (see the discussion in Harremoes and Madsen (1999)) and the work of Del Giudice et al. (2015a) demonstrated only limited improvement of the predictions beyond a certain level of model complexity.

The skill of the runoff forecasts (SPI, Fig. 4) was strongly reduced and varied more between events if radar rainfall forecasts were used as model input (scenario BU) instead of a perfect rainfall forecast derived from gauge measurements (scenario AU). The decrease in forecast skill was most pronounced for the smallest considered sub-catchment (WAM) and less pronounced for the larger sub-catchments such as KLO. This behaviour was caused by the shorter concentration time in smaller catchments, where a runoff forecast for 2 h into the future is strongly affected by the uncertainty of the rainfall forecast.

5.2. Reliability of runoff forecasts

Fig. 5 and Fig. 6 compare expected and observed coverage rates for forecasts of runoff volume on a 120 min horizon. We identified a
general tendency for the runoff forecasts to be unreliable. For example, a 90% prediction interval covered less than 70% of the observations in all of the sub-catchments in scenario AU. The main reason for this result was that the stochastic grey-box approach aims to model runoff forecast uncertainty for a multitude of forecast horizons in a single model structure. This approach has the advantage of providing us with an intrinsic quantification of the correlation between forecasts for different horizons, but the model structure is currently not adapted to account for the different effects occurring at different forecast horizons. Forecast variance increases nonlinearly from short forecast horizons (where the updating of the model to current observations has a strong influence on forecast quality) to longer forecast horizons (where uncertainty from rainfall input and model structure affects the runoff forecast most). The stochastic differential equations in Eq. (1), however, assume that forecast variance increases linearly with lead time because the variance of an increment \( \Delta \theta \) of the Wiener process driving the noise term directly corresponds to the considered time increment \( \Delta t \). As a result, the stochastic forecast models tended to be reliable on short forecast horizons and unreliable on longer forecast horizons (not shown, but demonstrated in Lowe et al., 2014b). We identified the following options for addressing this problem in the grey-box modelling framework in the future:

- Different forecast models could be applied for different forecast horizons. While this option would yield reliable forecasts, it would also lead to a strong increase in the number of parameters that need to be identified, and it would not provide the description of correlation between forecast horizons. The identification of forecast distributions of runoff volumes would then require the application of copulas (Madadgar et al., 2014; Papaefthymiou and Kurowicka, 2009) or recursive estimates of the correlation of forecast errors for different horizons (Löwe et al., 2014b; Pinson et al., 2009) to link the stochastic flow forecasts for different horizons.

- A scaling factor depending on forecast lead time could be introduced in the diffusion term of the state equations (Eq. (1))

![Fig. 5. Reliability diagrams (expected vs. observed coverage of the observations) for scenario AU (true (observed) rainfall input from gauges in runoff forecasting) for the different catchments. The results for the single events are marked in grey, while the median coverage rates over all events are marked as black, solid lines.](image-url)
and identified as a parameter in the automatic calibration routine. This option seems preferable, as it could be easily integrated in the grey-box modelling approach.

Another interesting result was that higher coverage rates were observed for scenario BU, where radar rainfall forecasts were used as input to the forecast models, than for scenario AU. The parameter estimation procedure identifies the uncertainty scaling for the model states \( s_i \) based on how many observations are located how far from the centre of the forecasted distribution (see Löwe et al. (2014b)). During rain periods, runoff forecast errors are much larger if radar rainfall is used as an input to the models, leading to a strong increase in the uncertainty parameters in the model and to increased forecast uncertainties. These, in turn, lead to an increased reliability of the model during dry weather periods, explaining the more reliable pattern observed in Fig. 6.

This issue can also be related to a deficiency in the structure of the stochastic grey-box model because only a single parameter \( s_i \) is used in Eq. (1) to scale the forecast uncertainty. Alternative formulations of the diffusion term should distinguish between dry weather and rain periods.

5.3. Forecast uncertainty and system-wide real-time control

The results shown in Fig. 8 indicate that there is a clear benefit in using forecast information in the system-wide control algorithm. All scenarios that apply forecast information (AU, ANU, BU and BNU) yield much lower overflow volumes and cost than the reference scenario REF.

In addition, accounting for the uncertainty of runoff forecasts in the system-wide control algorithm has proven beneficial. The reduction in total overflow cost (comparing scenarios AU and ANU as well as BU and BNU) was comparable in magnitude to the increase in total overflow cost caused by the uncertainty of radar rainfall forecasts (comparing scenarios AU and BU as well as ANU and BNU).

The results also showed some limitations of the setup. Replacing perfect rainfall forecasts (scenarios AU and ANU) by radar rainfall...
forecasts (BU and BNU) decreased runoff forecast skill and strongly increased runoff forecast uncertainty at KLO. This resulted in high forecasted overflow cost at this point and a prioritization of overflows from KLO over those from STP (see Fig. 3), strongly increasing overflow volumes at STP. Although the total overflow cost in the system could be reduced, such effects may be undesirable and can be mitigated by an adjustment of the CSO unit cost.

Generally, DORA prioritizes outflow from overflow points where runoff forecast uncertainty is high over overflow points where runoff forecast uncertainty is low. This is desirable because free storage volume is kept available at points where little is known about the future runoff, while storage volume at other control points is used to the fullest. It is, however, important that realistic estimates of forecast uncertainty are identified. In particular, combinations of over- and underestimation of forecast uncertainty at different control points are expected to negatively impact the performance of the control scheme.

5.4. General applicability of the setup

The aim of the article was to provide a proof of concept for a forecast- and optimization-based RTC setup that takes forecast uncertainty into account. The setup was demonstrated in a case study involving six different sub-catchments in which the performance of the runoff forecasting models was tested by comparing with observations. The process of generating stochastic runoff forecasts over a horizon of 2 h and identifying set points using the DORA algorithm required approximately 1 min on a standard PC (Intel i7-4930k) and is thus well feasible within a control time step of 2 min.

The sub-catchments had different sizes and structures (Table 1), and they therefore behaved differently hydraulically. In addition, flow observations were far from perfect and, in most of the catchments, were affected by changes in pumping discharges (Section 3.3.1 and Appendix C). These conditions correspond well
to what we would expect in other urban catchments. The skilful forecasts that were obtained for most of the sub-catchments suggest that the forecast setup can be transferred to other catchments.

Current limitations of the setup are that rather unreliable forecasts are obtained for long forecast horizons (Section 5.2) and that only a very simple model structure is considered, while including effects from, e.g., overflow structures located upstream from the control point may well improve the forecast skill in some sub-catchments (Sections 2.1 and 4.1). Conversely, the radar rainfall forecasts provided as model input in our case study were incomplete. In particular, no forecast information was available for horizons beyond 90 min. We would therefore expect somewhat better rainfall forecasts and thus better performance of the runoff forecasts in other catchments with more complete rainfall forecasts.

The derivation of inflow measurements using the water balance of the control points proved problematic in terms of operational reliability because each inflow measurement depended on the correct operation of multiple sensors. In fact, we were able to use only 98 out of 171 relevant rain events in our data period as a result of sensors failing at one or multiple control points. This problem can be avoided by installing redundant level sensors or dedicated flow measurements. Mannig and Lindenberg (2013) demonstrated that a reliable operation of a control system can also be achieved with a large number of 13 control points and more than 100 sewer measurements.

The effects of forecast uncertainty on the optimization-based control scheme were tested for the first time in an urban setting in this study. Raso et al. (2014) demonstrated the value of considering forecast uncertainty in reservoir operation. As we applied a full-scale catchment in our case study, our results provide a strong indication that optimization-based control schemes should consider forecast uncertainty. Nevertheless, this result needs to be verified in further studies and catchments.

6. Conclusions

A forecast-based, stochastic optimization setup was presented for system-wide real-time control of combined sewer systems aimed at reducing combined sewer overflows. The setup combined stochastic grey-box models for probabilistic forecasting of urban runoff online and the risk-based optimization algorithm DORA that accounts for forecast uncertainty and impact cost.

In a case study in Copenhagen, Denmark, involving 6 sub-catchments of varying sizes and 7 control points we assessed forecast performance by comparing runoff forecasts to measurements. In particular, no forecast information was available for horizons beyond 90 min. We would therefore expect somewhat better rainfall forecasts and thus better performance of the runoff forecasts in other catchments with more complete rainfall forecasts.

4. Models that forecast the inflow to the control points could be set up, although direct inflow measurements were not available for most control points. Inflow measurements were derived using the water balance of the storage basins and were in several cases strongly influenced by pumping discharges. The stochastic grey-box models were capable of handling the resulting noisy flow measurements. However, the considered measurements must be ensured to fully capture the water balance at a control point.

5. Stochastic runoff forecasting models need to consider a nonlinear increase of forecast uncertainty with forecast lead time when generating multistep forecasts.

6. Deriving flow measurements from a multitude of sensors implies that each measurement depends on the correct operation of multiple sensors. This can severely impact the reliability of the control setup, a problem that can easily be mitigated by installing redundant sensors in the most suitable locations during the implementation of the RTC system.

The present study has provided a proof of concept for considering forecast uncertainty in a risk-based optimization scheme for RTC of urban drainage systems. Future work should focus on improving rainfall forecasts as well as the development of libraries of runoff forecasting models, where the model structure performing best for a given control point can be selected automatically.

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Appendix A, B and C. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.envsoft.2016.02.027.

References


