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Title: A generalised Dynamic Overflow Risk Assessment (DORA) for Real Time Control of urban drainage systems

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Abstract

An innovative and generalised approach to the integrated real time control of urban drainage systems is presented. The Dynamic Overflow Risk Assessment (DORA) strategy aims to minimise the expected Combined Sewer Overflow (CSO) risk by considering (i) the water volume presently stored in the drainage network, (ii) the expected runoff volume (calculated by radar-based nowcast models) and – most important – (iii) the estimated uncertainty of the runoff forecasts. The inclusion of uncertainty allows for a more confident use of Real Time Control (RTC). Overflow risk is calculated by a flexible function which allows for the prioritisation of the discharge points according to their sensitivity and intended use. DORA was tested on a hypothetical example inspired by the main catchment in the city of Aarhus (Denmark). An analysis of DORA's performance over a range of events with different return periods, using a simple conceptual model, is presented. Compared to a traditional local control approach, DORA contributed to reduce CSO volumes from the most sensitive points while reducing total CSO volumes discharged from the catchment. Additionally, the results show that the inclusion of forecasts and their uncertainty contributed to further improving the performance of drainage systems. The results of this paper will contribute to the wider usage of global RTC methods in the management of urban drainage networks.

Keywords

Integrated urban water management, Overflow risk, Real-Time Control, Uncertainty, Radar-based flow forecast, Generalised approach.

1. Introduction

The Real-Time Control (RTC) of urban drainage systems is being increasingly applied to improve the performance of existing drainage networks. This is demonstrated by the increasing number of examples that can be found in the literature (e.g. Maeda et al. 2005; Fuchs and Beeneken 2005; Muschalla et al. 2009; Nielsen et al. 2010; Puig et al. 2009; Schutze and Haas 2010; Seggelke et al. 2013). Generally, RTC is applied in order to better exploit available storage capacity (reducing the risk of Combined Sewer Overflows (CSOs) and pluvial flooding) and to improve the management of WasteWater Treatment Plants (WWTP) during wet weather conditions (e.g. Heinonen et al. 2013). Additionally, RTC can also include the status of the receiving water body and other variables (such as energy consumption) in the optimisation scheme, as in the modelling studies presented by Vanrolleghem et al. (2005), Fu et al. (2008) and Langeveld et al. (2013), who used multi-objective functions to optimise integrated wastewater systems.

All of these examples stress the importance of RTC as a flexible and cost-effective tool which can help urban water managers to (i) meet stricter environmental regulatory requirements, (ii) fulfil the increasing demand from the general population for a higher level of service and (iii) cope with changes in precipitation patterns. For example, Dirckx et al. (2011) compared the cost and performance of RTC against other structural solutions (detention basins, disconnection of impervious areas, enlargement of pipes, etc.). Furthermore, RTC should be seen as a tool that integrates with structural solutions rather than act as an alternative thereto, thus decreasing the total investment that

urban wastewater utilities need to make in order to meet targets (also see the discussion in Beeneken et al. 2013).

RTC can benefit from information about future inputs and the resulting behaviour of the system based on the results provided by different models (this approach is also known as Model Predictive Control – MPC). Examples of models that can be applied for MPC in urban drainage systems are radar-based rainfall nowcast models, hydrodynamic models nowcasting flow in drainage networks (Liguori et al., 2012; Ocampo-Martinez and Puig, 2010; Thorndahl et al., 2013), and models estimating the maximum flow allowed through the secondary clarifier in the WWTP. Gaborit et al. (2012) used rainfall predictions combined with a water quality model to optimise the performance of a stormwater detention pond.

The benefits of MPC in integrated MPC have been shown in literature for both rural and urban drainage systems (see e.g. Lobbrecht, 1997; Rauch et al., 1999a,b), but current full-scale application of MPC in urban areas are limited to just a few examples (Fradet et al. 2011; Pleau et al., 2005; Puig et al. 2009). The urban drainage models needed for MPC are, in fact, affected by several sources of uncertainty (Schutze et al. 2004; Deletic et al. 2012; Campisano et al. 2013, for example, addressed this issue from different perspectives), which limits the current full-scale application of MPC to just a few examples (Fradet et al. 2011; Puig et al. 2009). Achleitner et al. (2009) presented an example of integration between a radar-based rainfall model and a hydraulic model and underlined the impact that uncertainty in the rainfall model had on the overall performance of the model. In order to reduce the impact of rainfall nowcast uncertainty, Fiorelli et al. (2013) proposed an approach which relies on frequent state updating and the use of medium to long-term forecasts (which have a lower level of uncertainty). However, input uncertainty still remains the major obstacle for the wider application of MPC, and several approaches for dynamically estimating rainfall runoff forecast uncertainty have been presented recently (see, for example, Löwe et al. 2013).

The inclusion of model uncertainty in decision making processes has been applied at the river basin scale and for river flood management. Coccia and Todini (2011), for example, illustrate examples

where uncertainty in river flow predictions can be integrated into a flood warning system. In urban systems, however, model uncertainty is increasingly taken into account for off-line models, used to design and evaluate the performance of drainage systems, but it is not known to be considered when controlling the system in real time.

This article introduces the Dynamic Overflow Risk Assessment (DORA) approach, which was developed to actively include uncertainty in the MPC of urban drainage systems and to fully exploit the potential of MPC approaches. DORA is a global control strategy which considers an estimated level of uncertainty in urban runoff predictions and then utilises this information to reduce expected overflow costs across the entire catchment. The potential of DORA to contribute to CSO reduction was benchmarked against traditional local control strategies in a theoretical catchment inspired by a real system. The theoretical results presented in this study provide the background for the full-scale application of DORA in different urban areas, representing the first step towards a widespread application of MPC tools in the management of urban drainage networks.

2. Methodology

2.1. Definitions

The Dynamic Overflow Risk Assessment (DORA) approach is a global optimisation strategy which uses a simplified representation of urban drainage networks. Only storage units are considered in the control strategy, and travel times between the nodes of the network are neglected in this first version of DORA. An overflow cost is assigned to each node of the network, thus reflecting the sensitivity of the receiving water body and enabling the prioritisation of the CSO discharge points (see section 2.3.1).

Each i -th detention basin of volume $V_{B,i}$ [m³] can be schematised as described in Figure 1a. Inflow to the basin is represented by the sum of (i) the flow from the upstream basins (lumped into $Q_{in,i}$ [m³/s]) and (ii) the forecasted runoff $Q_{F,i}$ [m³/s], which accounts for the runoff from the i -th sub-catchment (of

area A_i [m^2]). The latter is calculated by a simple rainfall-runoff model based on measured and forecasted rainfall.

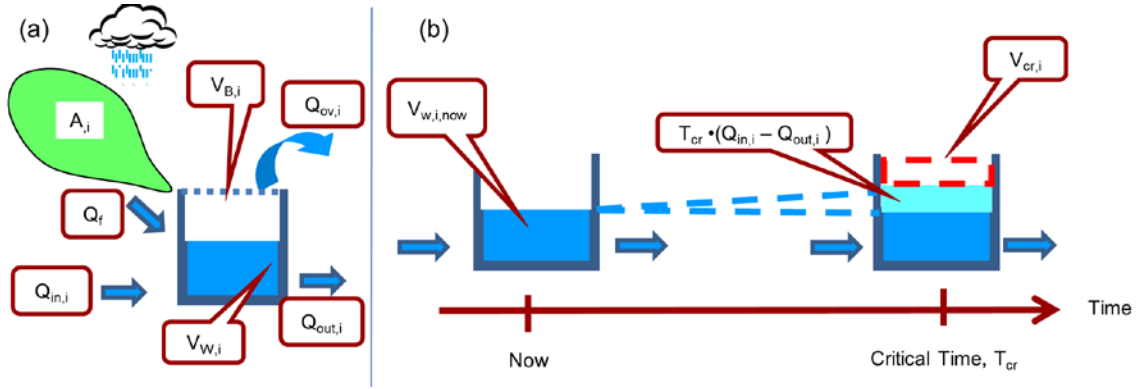


Figure 1. (a) Schematic diagram of a detention basin; (b) representation of critical volume $V_{Cr,i}$.

Outflow $Q_{out,i}$ [m^3/s] can be either fixed (as in the case of a connection to a wastewater treatment plant) or regulated by the control strategy. When the total inflow to the basin (the sum of $Q_{in,i}$ and $Q_{f,i}$) exceeds outflow capacity $Q_{out,i}$, water (expressed as $V_{w,i}$ [m^3]) is stored in the basin until the storage capacity is filled and exceeding flow $Q_{ov,i}$ [m^3/s] is discharged by the overflow structure.

The RTC strategy operates within critical time T_{cr} [s], here defined as the time that the runoff which is forecasted across the entire catchment would take to fill the available total storage volume (if this was all located at one point). This can be expressed in mathematical terms as:

$$\int_{now}^{T_{cr}} \sum_{i=1}^{N_{basins}} Q_{F,i}(t) dt = \sum_{i=1}^{N_{basins}} (V_{B,i} - V_{w,i}) \quad (1)$$

According to this formulation, T_{cr} marks the instant when all the forecasted runoff equals the total vacant storage volume in the system, in which case the RTC strategy has no more capacity to avoid overflow. The critical time thus represents the time until overflow, assuming that all storage capacity was located at one point and that there were no transport capacity limitations confining the real-time control strategy. The critical time is thus shorter for high-intensity rain events, i.e. when there is little

time to act. This formulation, which resembles the Central Basin Approach proposed by Einfalt and Stölting (2002) to calculate the maximum theoretical RTC potential, might show some limitations in the case of very intense and localised rainfall, which might result in the quick utilisation of the available storage in a single detention basin (and thus in the identification of non-optimal flows for that specific point). In addition, it does not consider the additional capacity provided by transportation through the drainage network.

Critical volume V_{cr} [m³] is defined for each detention basin individually as (Figure 1b):

$$V_{cr,i} = V_{B,i} - V_{w,i,now} - \int_{now}^{T_{cr}} (Q_{in,i}(t) - Q_{out,i}(t)) dt \quad (2)$$

where $V_{w,i,now}$ [m³] is the volume of water currently stored in the basin, and where the last term in Eq. 2 represents the variation in water volume until T_{cr} . When T_{cr} is greater than the forecasted time horizon T_{hor} [s], T_{cr} is substituted by T_{hor} . This limits the influence of the forecast on the control to the time interval when the forecasts are reliable. T_{hor} thus depends on the method that is used to generate the forecasts. For example, the forecast horizon for radar-based forecasts commonly used in the Danish context is commonly assumed to be 2 hours, while T_{hor} for forecasts generated by numerical weather prediction models can be longer (see Thorndahl et al., 2013).

Assuming that $Q_{in,i}$ and $Q_{out,i}$ are constant (i.e. when the system is not controlled and the flow between nodes does not change), Eq. 2 can be rewritten as:

$$V_{cr,i} = V_{B,i} - V_{w,i} - (Q_{in,i} - Q_{out,i}) \cdot T_{cr} \quad (3)$$

2.2. Dynamic Overflow Risk Assessment

2.2.1. DORA inputs

The DORA strategy was developed based on the following available information:

- (i) *Stored water volumes in the system.* These data are provided by sensors installed in the system (water levels, flow at the inlet and outlet of basins), and they resemble the information which is used by traditional RTC approaches.

- (ii) *Expected runoff volumes.* This information is provided by rainfall-runoff nowcast models, which enable MPC of the drainage network (as outlined in Rauch and Harremöes (1999a). However, nowcasts are affected by high levels of uncertainty, which can significantly limit the efficacy of this input.
- (iii) *Uncertainty of the runoff forecasts.* Considering the uncertainty of runoff predictions in the control scheme allows DORA to exploit information provided by runoff nowcasts, but without being limited by high uncertainty. This feature represents the main difference between DORA and other MPC approaches presented in the literature (see, for example, Schuetze and Muschalla, 2013), as it allows one to use a piece of information which was previously discarded.

2.2.2. DORA global cost function

Thanks to the ability to consider forecast uncertainty, DORA does not minimise the expected *CSO volume*; rather, it aims at minimising a *CSO risk function*, which is expressed in monetary or monetary-proportional terms by using a global cost function. This function can be used to integrate different objective functions (e.g. overflow volumes – as in this study –, pollutant loads, energy consumption, electricity prices flooding risk) into monetary or monetary-proportional terms. Therefore, DORA can theoretically be used for a wide range of approaches (emission- or immission-based approaches, integrated approaches considering the status of receiving waters, etc.) by modifying the cost function according to the desired objectives. Thus DORA – when feasible – represents a simple surrogate for more complex multi-objective optimisation algorithms (such as the one used in the example presented by Fu et al., 2008).

The overflow cost employed in this study considers only CSO volumes, as the primary objective in the controlled catchments (see Section 2.3.1) is the protection of bathing waters, followed by a reduction of pollutant loads discharged into the environment.

According to this formulation, the CSO costs occurring in each *i-th* basin can be subdivided into three terms:

$$Cost = \sum_{i=1}^{N_{basin}} (C_{cr,i} + C_{F,i} - C_{hor,i}) \quad (4)$$

The first term relating to CSO cost ($C_{cr,i}$) refers to overflows generated by water volumes already in the drainage network (e.g. overflow caused by flow from upstream sub-catchments), the second term ($C_{F,i}$) expresses cost due to expected runoff during the time interval defined by the forecast horizon (critical time as outlined above) and the third term is a factor which tries to maximise available storage volume beyond the forecast horizon T_{hor} . A detailed description of the terms is presented in the following sections. Additional control objectives (such as reduction of flooding risk, energy consumption, impact on receiving waters) can be included in the optimization schemes by adding additional cost terms to Eq. 4.

2.2.3. Overflow cost due to flows from upstream sub-catchments

The first term in Eq. 4 is associated with overflows caused by water volumes already in the system and by flows between detention basins (calculated by using $Q_{in,i}$ and $Q_{out,i}$): here, the information used by DORA resembles that employed by traditional RTC approaches. When water volume discharged from the upstream network ($Q_{in,i} \cdot T_{cr}$) minus the discharge to downstream parts of the network ($Q_{out,i} \cdot T_{cr}$) exceeds available storage volume ($V_{B,i} - V_{w,i}$), critical volume V_{cr} (Eq. 3) is negative and corresponds to the inevitably incurred overflow volume for that particular set of flows between basins. This overflow cost, $C_{cr,i}$, is thus calculated as:

$$C_{cr,i} = \begin{cases} c_i \cdot (-V_{cr,i}) & \text{for } V_{cr,i} < 0 \\ 0 & \text{for } V_{cr,i} \geq 0 \end{cases} \quad (5)$$

where c_i is unitary overflow cost [€m^3] for the i -th basin, which is defined according to the sensitivity of the recipient.

2.2.4. Overflow cost due to forecasted runoff in the local sub-catchment

The second term in Eq. 4 considers the costs associated with overflows caused by the forecasted runoff volume V_F , in the i -th sub-catchment, which is calculated as:

$$V_{F,i} = \int_{\text{now}}^{T_{cr}} Q_{F,i}(t) dt \quad (6)$$

The various sources of uncertainty affecting runoff flow predictions also affect the estimation of runoff volume $V_{F,i}$ (as illustrated in Figure 2a): different runoff predictions can lead to different values of $V_{F,i}$. Therefore it is possible to associate a probability value $p(V_{F,i})$ to the expected runoff volume. In Figure 3a, for example, the value of V_F with the highest probability corresponds to the integral of the most probable runoff prediction (solid line in Figure 2a). Overflow risk is then estimated by using the following formula:

$$C_{F,i} = \int_{V_{CR,i}}^{\infty} C(V_{F,i}) \cdot p(V_{F,i}) dV_{F,i} \quad (7)$$

where $C(V_{F,i})$ is the cost expressed as a function of the forecasted overflow volume (Figure 3b). The probability distribution of the forecasted runoff is defined by the estimated uncertainty of the rainfall-runoff model (thus lumping together input uncertainty – from weather forecasts/rainfall nowcasts – model parameter and structural uncertainty). The risk therefore varies at each time step, i.e. every time a new runoff prediction is available.

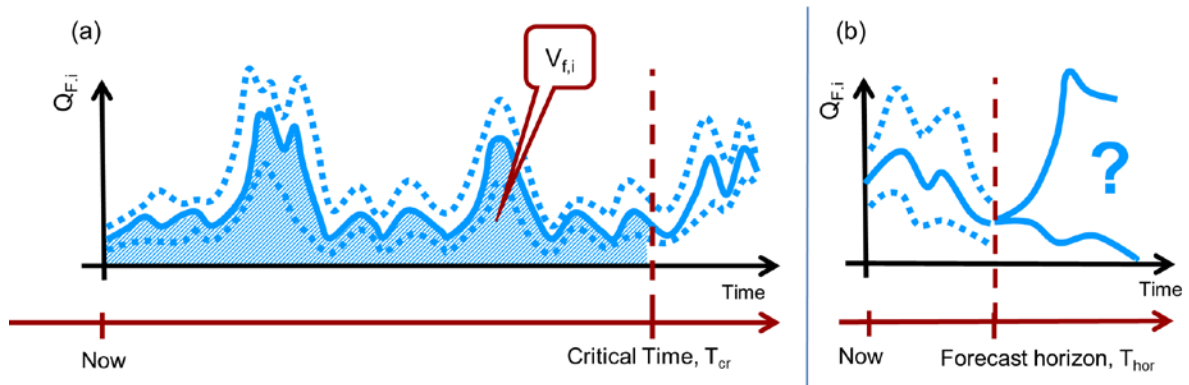


Figure 2. (a) Schematic representation of forecasted runoff volume V_F (hatched area) and respective uncertainty bounds; (b) possible development of runoff beyond the forecast horizon T_{hor} .

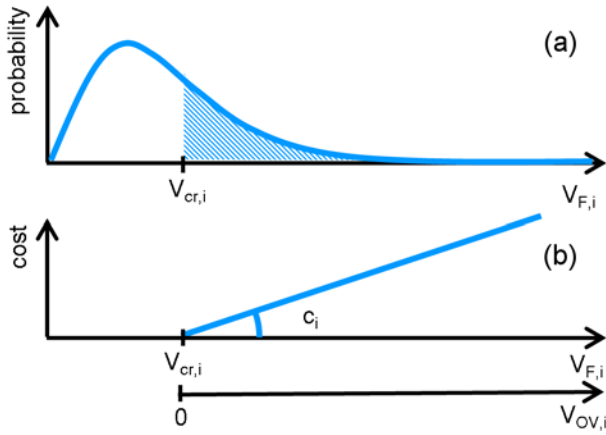


Figure 3. (a) Probability distribution of forecasted runoff volume V_F , where the hatched area represents the total probability of the overflow; (b) associated overflow cost function, as used in Eq. 7.

Depending on the complexity of the expressions of cost as a function of overflow volume ($C(V_{F,i})$), and on the uncertainty of the forecasted runoff volume ($p(V_{F,i})$), the integration in Eq. 7 may be solved analytically or numerically. An analytical solution, for example, is possible (i) if the cost of the overflow is linearly proportional to the overflow volume (as in Figure 3b) and (ii) if the probability of the forecasted runoff volume $p(V_{F,i})$ follows a known probability density function. In this study, $p(V_{F,i})$ was assumed to always follow a gamma distribution. Although the latter assumption provides a realistic shape for the highly non-Gaussian probability of runoff predictions, it should be noted that preliminary investigations suggest that the gamma distribution tends to overestimate uncertainty associated with the runoff forecast (Löwe et al., 2013). Both of these assumptions, however, have been considered appropriate for this study and for an initial formulation of DORA.

2.2.5. Discount function

The overflow risk considered by Eq. 7 is based on the known level of uncertainty in the runoff predictions. However, runoff beyond the forecast horizon T_{hor} is also uncertain (Figure 2b), and in addition it will influence the optimal control actions because the emptying times of the detention basins will most often be longer than the available runoff forecast horizon. At the present stage, uncertainty in runoff beyond T_{hor} is not quantified (according to the uncertainty level classification

presented by Warmink et al. (2010), T_{hor} represents the limits for qualitative uncertainty). DORA accounts for this qualitative uncertainty by using the discount term $C_{hor,i}$ in Eq. 4. This discount term is defined by the following equation:

$$C_{hor,i} = \frac{k_{hor}}{c_i} \cdot f(\phi_i) \cdot g(\Delta Q_{opt,i}) \quad (8)$$

where k_{hor} [-] is the discount factor, $f(\phi_i)$ a smooth switch function which activates the discount function only when the basin is almost empty (below 10% filling) and $g(\Delta Q_{opt,i})$ a function aiming at ensuring the fast emptying of a basin.

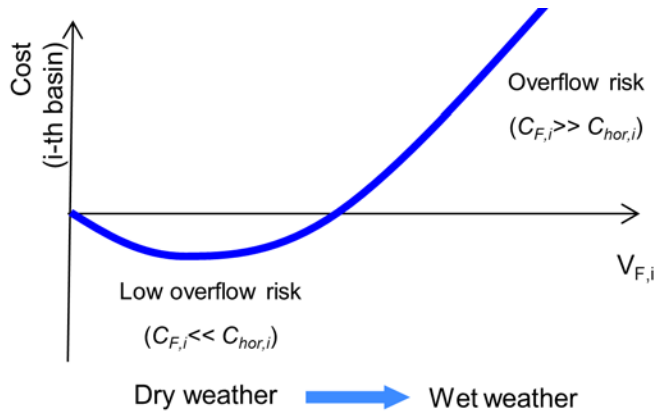


Figure 4. Sketch of the influence of the overflow risk ($C_{F,i}$) and the discount factor ($C_{hor,i}$) on the total cost calculated for a generic basin as a function of the increasing forecasted volume ($V_{F,i}$).

The k_{hor} [-] parameter defines the magnitude of the discount, which is in the order of magnitude of 10^{-6} - 10^{-8} , i.e. $C_{hor,i}$ plays a role in system optimisation, but only when the basins are almost empty and the overflow risk is low (as sketched in Figure 4). When only dry weather flow is present, the overflow risk (calculated by Eq. 7) is low (around 10^{-9} - 10^{-10}) and the employed search algorithm may become numerically unstable and lead to sub-optimal solutions. The “discount” term, $C_{hor,i}$, is therefore introduced to identify optimal flows when forecasted runoff volumes are low.

The switch function $f(\phi_i)$ is defined as:

$$f(\phi_i) = 1 - \frac{\phi_i^4}{n^4 + \phi_i^4} \quad (9)$$

where ϕ_i [-] is the filling degree of the i-th basin and n [-] is a parameter that corresponds to the inflection point of the switch function (set to 0.05).

Function $g(\Delta Q_{opt,i})$ is designed to give a higher discount to the sets of flows between detention basins that minimise the difference $\Delta Q_{opt,i}$ [m³/s], calculated as the difference between the proposed basin outflow (Q_{out}) and optimal outflow from the basin $Q_{out,opt}$ [m³/s].

Function $g(\Delta Q_{opt,i})$ is calculated as:

$$g(\Delta Q_{opt,i}) = \exp \left(- \frac{\left(\frac{Q_{out,i} - Q_{out,opt,i}}{Q_{out,opt,i}} \right)^2}{0.5} \right) \quad (10)$$

The maximum discount is thus achieved for an empty basin when Q_{out} equals optimal flow $Q_{out,opt}$. The latter is calculated as the flow required to convey downstream all the water volumes expected at the basin:

$$Q_{out,opt,i} = \frac{V_{W,i} + V_{F,i} + \alpha \cdot Q_{in,i} \cdot T_{cr}}{T_{cr}} \quad (11)$$

where α [-] is a safety factor which accounts for uncertainty in the flows coming from the upstream basins (e.g. due transport time in the pipes). According to this formulation, the optimal outlet flow from the basin takes into account upstream flow, dry weather flow and the contribution of the upstream part of the catchment. When optimal flow is achieved (i.e. $\Delta Q_{opt}=0$), there is no excess storage capacity in the basin.

Overall, the use of the discount factor resembles a traditional rule-based RTC approach, as it assigns a lower cost to the control settings, therefore ensuring the faster emptying of basins. Moreover, this ensures that the basin can cope with unforeseen heavy rain events beyond the forecast horizon.

2.2.6. Minimising the global cost function

Real-time control based on DORA involves identifying the flows between detention basins and WWTP (i.e. the values of $Q_{in,i}$ and $Q_{out,i}$ for each i -th basin) that minimise the global cost function defined by Eq. 4. Optimal flows are identified by using a genetic algorithm (based on the JGAP software package -), selected from among different search algorithms (including Downhill Simplex, Powell's and Quasi-Newton optimisations) and based on the discussion presented in Rauch and Harremoës (1999a,b) and the results obtained by Fu et al. (2008). Although the genetic algorithm requires a large number of function evaluations, it consistently ensures the minimisation of the global risk function also with a highly non-linear and discontinuous response surface typical of multi-objective optimisation in urban drainage networks.

2.2.7. The control cycle

In practice the DORA control strategy is applied within a control cycle involving the following steps:

1. For each basin, current water volume in the detention basins is observed ($V_{w,i}$);
2. weather radar precipitation nowcasts are used to generate flow predictions for each detention basin (obtaining $Q_{f,i}$, which is integrated to obtain $V_{f,i}$);
3. the genetic search algorithm is used to find the set of optimal flows between detention basins that minimises the cost function (Eq. 4);
4. the actuators in the catchments are set to achieve the desired flows between detention basins ($Q_{out,i}$ calculated in the previous time step).

In this study this entire control cycle was repeated every two minutes, corresponding to the frequency used to collect measurements in the system.

2.3. Evaluation of DORA's performance

2.3.1. Simplified Marselisborg catchment

An integrated control is being implemented in the Marselisborg catchment, located in the city centre of Aarhus (Denmark – see also Benedetti et al., 2013), with a primary focus on improving and protecting bathing water status, and a secondary focus on reducing pollutant emissions into the environment. To illustrate the behaviour of DORA, and to benchmark its performance against local RTC, DORA was applied to a theoretical example, inspired by the Marselisborg catchment (Figure 5). This approach follows the benchmarking methodology presented in Borsanyi et al. (2008), as using simplified virtual systems allows for identifying the advantages and deficiencies of different RTC strategies. Compared to the real system, the hypothetical example portrayed simplified hydraulic behaviour with regards to hydrodynamics, the operation of pumping stations and actuators in the system. For example, an average velocity of 1 m/s was assumed for flow in pipes, i.e. the residence time in each connection is linearly dependent on the length of the connection. Also, different areas connected to the Carl Blocks Gade (CB) detention basin were lumped into a single catchment.

The total reduced area is about 280 ha, subdivided into eight sub-catchments of different sizes (Table 1). The total storage capacity in the system is about 43,200 m³, subdivided into six detention basins and two pumping stations with limited storage volume (JP and MR - Figure 5). The runoff from the eight sub-catchments ($Q_{F,i}$) was calculated by using a time-area method and the concentration times listed in Table 1. The CB sub-catchment discharges into the Moelle Parken (MO) basin during dry weather periods, while the flow from the CB basin can be subdivided between the Film Byen basin (FI) and the Jaergergaards Gade (JP) pumping station. The Marselisborg WWTP, which is located downstream of the modelled catchment, has a capacity of 200,000 PE, with a maximum flow capacity of 1.4 m³/s. The basins' overflow structures discharge into the Aarhus Stream or into Aarhus harbour: different costs are thus assigned to the each overflow structure according to the vulnerability of the recipient (Table 1), with the highest priority assigned to Havnen, where bathing areas are located.

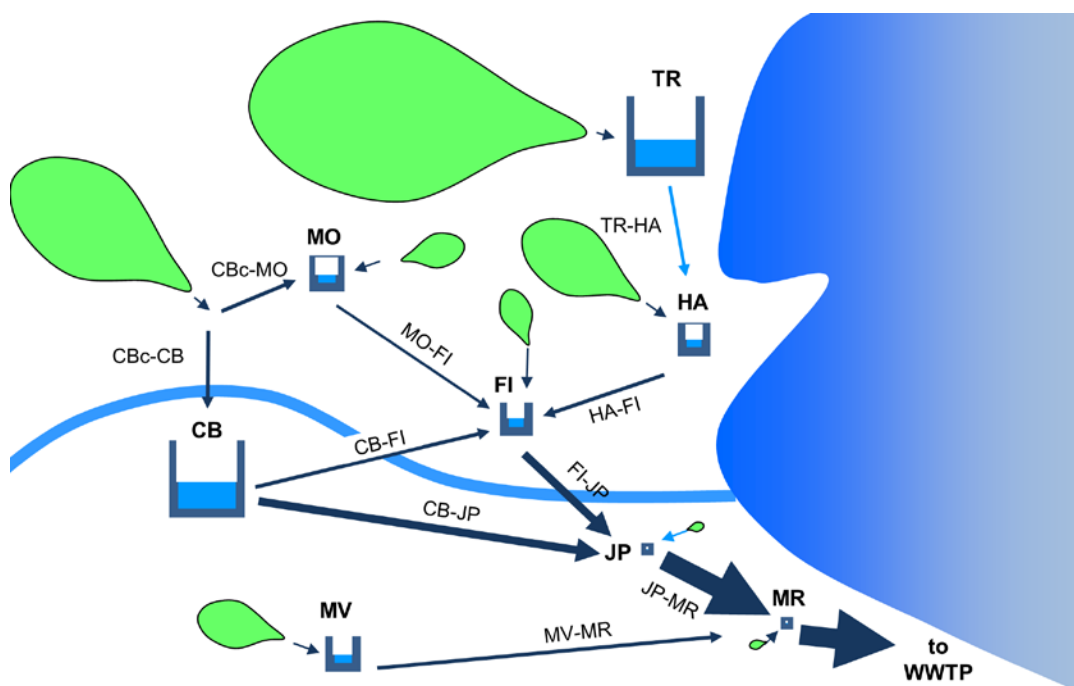


Figure 5. Scheme of the simplified Marselisborg catchment.

Table 1. Key data for the Marselisborg catchment used in the study.

| Sub-catchment | Red. Area [ha] | Concentration time [s] | Basin Volume (V_B) [m ³] | Dry weather flow [l/s] | CSO Price [EUR/m ³] | Downstream connection | |
|-------------------------|----------------|------------------------|--|------------------------|---------------------------------|-----------------------|------------------------------|
| | | | | | | Length [m] | Max Qout [m ³ /s] |
| | | | | | | 760 ^a | 0.65 ^a |
| Carl Blocks Gade (CB) | 64 | 900 | 15200 | 64.5 | 2,8 | 1720 ^b | 0.40 ^b |
| | | | | | | 2120 ^c | 1.50 ^c |
| Moelle Parken (MO) | 18.5 | 490 | 1500 | 18.7 | 6.4 | 1120 | 0.30 |
| Film Byen (FI) | 16.4 | 450 | 3600 | 16.5 | 6.4 | 320 | 1.30 |
| Troejborg (TR) | 102 | 1150 | 16000 | 103 | 4.6 | 1280 | 0.30 |
| Havnen (HA) | 40 | 715 | 3200 | 40.3 | 10 | 1000 | 0.36 |
| Jaergergaards-gade (JP) | 5 | 250 | 100 | 5.04 | 2.8 | 650 | 1.36 |
| Morvads Vej (MV) | 27 | 580 | 3600 | 27.2 | 8.2 | 2800 | 0.20 |
| Marselisborg WWTP (MR) | 5 | 250 | 10 | 5.04 | 1.0 | - | 1.40 |

^a Connection to MO; ^b Connection to FI; ^c Connection to JP

The Marselisborg catchment was simulated by using the WaterAspectsTM hydrological model (Grum et al., 2004), which allows for a simplified representation of the drainage network (e.g. rainfall-runoff processes are simulated through the time-area method, while a simple transport function is used for pipes) and resembles similar models (such as SIMBA[®] used, for example, in Erbe and Schuetze, 2005) or CITYDRAIN[®] (Achleitner et al., 2007). Given the hypothetical nature of the simulated catchment, the model was not calibrated and the parameters listed in Table 1 were used.

Five years' rainfall data (from 1991 to 1995) were retrieved from the rain gauge located at the Viby J. WWTP, belonging to the Danish Water Pollution Committee network and operated by the Danish Meteorological Institute (Jørgensen et al., 1998). In this study runoff forecasts were obtained by using the recorded rainfall data (thus using “perfect” forecasts, with derived runoff forecast uncertainty represented by the gamma distribution) distributed uniformly across the catchment. Overflow events were identified by running the model with the five-year rain data and by ranking the events according to the total overflow volume. To better assess the performance of the RTC strategy, an overflow event was defined as an event occurring at least 8 hours after the previous event – a value which was defined according to the characteristics of the catchment. In fact, the system is expected to be in a dry weather operating condition after 8 hours (with the exception of TR, which requires more than 22 hours to be emptied). As a result of this definition, a single overflow event can include several rain events of different magnitude. Likewise, note that the frequency of the overflow event does not necessarily correspond to the frequency of the rain event(s) which generated it (as in the case of overflow events caused by coupled rain events).

2.3.2. Comparison of RTC approaches

The performance of the DORA control strategy was evaluated by comparing four different scenarios:

- (a) *Baseline*: drainage network without any flow controls.
- (b) *Traditional local RTC approach*: a local control was applied to reduce the difference between the filling degree of the basins ($\Delta\theta$). This “equal filling degree” strategy is widely applied (see

among others Borsanyi et al. 2008 and Dirckx et al. 2011), but it does not account for different basin sensitivities. It was included in

- (c) this study by minimising the weighted difference in filling degree $\Delta\theta^*$, which was defined as:

$$\Delta\theta^* = \theta_{up}^{\frac{c_{up}+c_{down}}{2c_{up}}} - \theta_{down}^{\frac{c_{up}+c_{down}}{c_{down}}} \quad (12)$$

where θ_{up} and θ_{down} are the filling degrees of the upstream and downstream basin, respectively, and c_{up} and c_{down} are the unitary CSO costs for the upstream and downstream basins, respectively. Thanks to this formulation, more sensitive basins are filled at a lower rate and emptied faster than less sensitive basins.

- (d) *DORA without forecast*: the drainage network was optimised by only using information regarding dry weather flow and present water volumes (i.e. V_{fi} was set to zero).
- (e) *DORA*: the proposed control strategy was applied by including runoff forecasts in the optimisation of the system.

2.3.3. Sensitivity Analysis

DORA employs a total of three parameters: overflow cost c_i (mainly affecting wet weather periods) and the two parameters k_{hor} , and α , which mainly affect dry weather periods (when no rainfall is expected within the forecast horizon) and the emptying of the basins (controlling the flow when the filling degree is lower than about 10-5%). To provide general guidelines for the application of DORA it was necessary to investigate the effect of these parameters on the overall performance of the system. This was achieved by performing a local sensitivity analysis of DORA parameters.

As the individual costs for single basins c_i are defined according to the importance of each discharge point, the analysis focused on the possible scales that can be used to prioritise the different basins in the system, rather than the exact numerical values associated with c_i . These scales are defined by water managers, i.e. the absolute values are not part of the analysis presented in this study. However, it is possible to assess how the different relationships between the discharge points (i.e. the scales that are

used to define the costs – see e.g. Figure 6) can affect the performance of DORA. In this study four different cost scales were compared (Table 2):

- (a) Equal cost: all the discharge points have equal importance, i.e. overflow volume and cost are equivalent.
- (b) Low-High scale: this three-level scale subdivides the discharge points into three sensitivity levels, corresponding to low-medium-high sensitivity to discharge.
- (c) Linear scale: the overflow points are divided into six classes, with overflow cost linearly increasing in line with overflow sensitivity. This classification is currently applied by the Aarhus municipality in the Marselisborg catchment.
- (d) Exponential scale: this scale is derived by the six-level scale, but c_i increases exponentially in line with the sensitivity of the discharge point.

The influence of the discount function was assessed by performing a local sensitivity analysis of the two parameters driving the discount function (k_{hor} , α). A total of 10 samples (linearly spaced for α and logarithmically spaced for k_{hor}) were sampled from the ranges listed in Table 3, which were defined based on typical CSO risk during dry weather periods (usually below 10^{-4}) and maximum uncertainty (20%) for flows from upstream basins. The analysis focused on the estimated CSO volume for the 30 largest overflow events over the simulated five-year period.

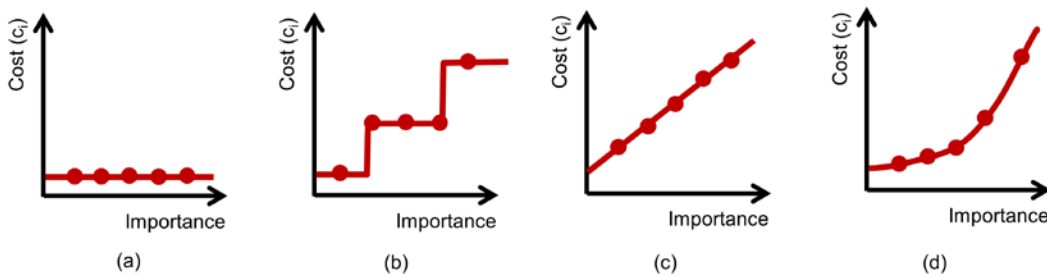


Figure 6. Different cost scales used to distinguish between the importance of the different discharge points: equal cost (a); low-high (b), linear (c) and exponential (d).

Table 2. Numerical values of c_i assigned to the different cost scales (Figure 6).

| Sub-catchment | Equal cost | Low-high scale | Linear scale | Exponential scale |
|-------------------------|------------|----------------|--------------|-------------------|
| Carl Blocks Gade (CB) | 1 | 1 | 2.8 | 1.15 |
| Moelle Parken (MO) | 1 | 5 | 6.4 | 2.11 |
| Film Byen (FI) | 1 | 5 | 6.4 | 2.11 |
| Troejborg (TR) | 1 | 5 | 4.6 | 1.43 |
| Havnen (HA) | 1 | 10 | 10 | 10 |
| Jaergergaards-gade (JP) | 1 | 1 | 2.8 | 1.15 |
| Morvads Vej (MV) | 1 | 10 | 8.2 | 4.36 |
| Marselisborg WWTP (MR) | 1 | 1 | 1.0 | 1 |

Table 3. Parameter intervals used in the local sensitivity analysis.

| Parameter | Min | Max | Description |
|-----------|-------------------|-------------------|--|
| k_{hor} | $1 \cdot 10^{-9}$ | $1 \cdot 10^{-4}$ | Defines when DORA changes from CSO risk minimisation to basin emptying |
| α | 1.0 | 1.2 | Safety factor for uncertainty in the flows coming from the upstream basins |

3. Results and discussion

3.1. Comparison of RTC approaches

The simulated overflow volumes and associated costs for the 30 largest CSO events (i.e. with a return period T_r from five to 0.17 years) are shown in Figure 7. Generally, all the simulated controls succeeded in reducing overflow volume and costs from the most sensitive outlet (e.g. total overflow volumes in HA are reduced by 50-60% by all the approaches). Figures 7c and 7d show how the performances of all the control methods were strongly dependent on the characteristics of the rain

event: as expected, a larger percentage improvement was obtained for more frequent (and thus smaller) rain events. However, strong variability was noticed between overflow events of similar magnitude. While an isolated rain event and a rain event comprising two or more coupled rainfalls can lead to similar overflow volumes, the effect of control will generally be much greater in the coupled event, where there is more time to act between the coupled events. This result stresses the importance of analyses based on long-term time series when assessing the performance of RTC approaches, rather than focusing on a limited number of rain events.

The local control strategy showed contrasting results. For example, the control at HA was designed to close the TR-HA connection and to empty the HA basin when water starts to accumulate in HA (see Eq. 12), thus protecting the highly sensitive basin. This resulted in a greater discharge from both the upstream and downstream low sensitive points (TR and JP, respectively; see also Figure 8), and a general increase in total CSO volume compared to the baseline scenario (+24% for the sum of the 25 events). However, when looking at the total cost, the decrease in CSO volume from the sensitive basins resulted in a decrease in the total costs for more frequent events ($T_r < 0.5$). Figure 7d shows that the local control obtained a reduction in CSO costs, but only for small-medium events ($T_r < 0.33$), suggesting that not all of the system's storage capacity was used as in the other scenarios. This emphasises the need for a better design of local controls and/or for a global control strategy which tries to exploit storage capacity in the network as a whole.

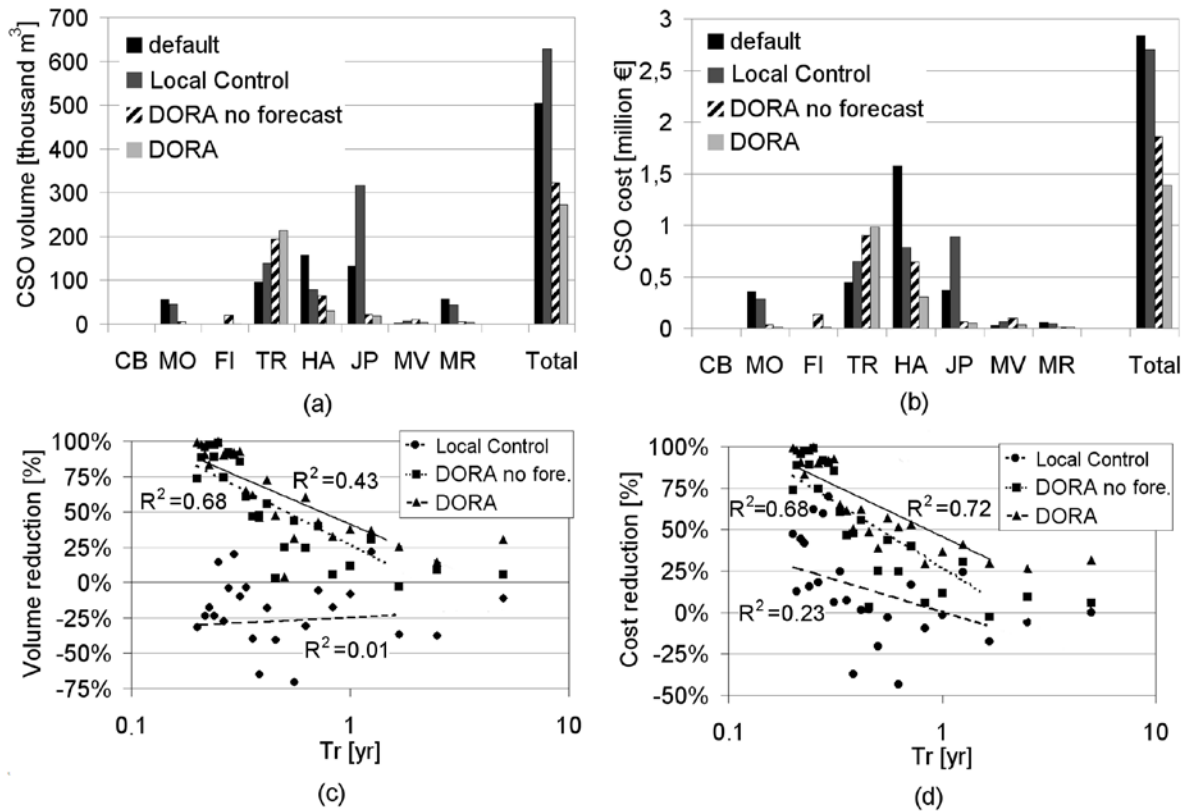


Figure 7. Simulation results for the 30 largest CSO events in the period 1991-95: (a) sum of CSO overflow volumes for all the discharge points, (b) sum of CSO overflow cost for all the discharge points, (c) reduction of total CSO volume (sum over all the CSO structures – y-axis) for individual events against their estimated return period (x-axis) and (d) reduction of total CSO cost (sum over all the CSO structures – y-axis) for individual events against their estimated return period (x-axis).

It is important to stress that the traditional RTC approach can be optimised further by improving control rules in various parts of the system; for example, controls can be tuned to reduce CSOs at JP overflow structure. The tuning of the local RTC strategy, however, is time-consuming and represents an important drawback compared to the fast implementation required by DORA.

DORA achieved a reduction in CSO volumes and costs, both without and with runoff forecasts. This was achieved not only by reducing the CSO volume in sensitive areas (up to an 85% reduction in HA), but also by holding more water in the upstream basins and by protecting the downstream part of the

catchment (as can be seen by the 85-90% reduction in JP and MR). The better exploitation of the storage capacity in the systems is also shown by the increase in the overflow from the upstream CSO structures, such as FI, MO and MV. Overflow in TR was more than doubled in order to protect the downstream HA basin (see Figure 8).

The benefit of including runoff forecasts, and the related uncertainty in the estimation of the volume, is exemplified by the trend lines in Figures 7c and 7d, whereby a greater reduction in CSO volume and costs is in fact achieved in the last scenario where flow forecasts are included. DORA without forecasts tended to protect downstream basins (e.g. JP) by storing water in directly upstream basins (e.g. FI); in this case DORA acts in a similar manner to a traditional local RTC approach, as the emptying of basins is controlled solely by the degree of filling. Even excluding flow forecast, the global approach ensured a greater reduction of CSO impact than local RTC. The addition of forecasts resulted in an increased exploitation of storage capacity in the upstream part of the catchment (mainly TR and CB – with the majority of overflow volume and cost caused at TR – see Figure 8). In this case, DORA protected downstream and more expensive basins by filling upstream basins earlier compared to the scenario without a forecast. While forecasts provided better improvements for medium-big events, adding forecasts increased CSO volume for a few small events. In these cases, storage in upstream basins reached 90-95% filling without forecasts, while with forecasts the maximum storage was exceeded to protect downstream basins. However, when looking at the sum of CSO volume discharged from TR and HA, the total reduction was around 4% compared to the baseline scenario. Overall, the use of forecasts resulted in a 13% greater reduction of CSO costs for the entire catchment (compared to the baseline scenario) than DORA without forecasts. From Figure 7 and Figure 8 it is evident that DORA managed to reduce overflows in the majority of the system (i.e. better exploiting available storage capacity), with the remaining CSO volume and costs concentrated in the TR-JP branch of the system (where the physical characteristics of the system, namely storage volumes and pipe capacity, limit the efficiency of RTC).

Given the simplified nature of the simulated system, the applicability to real systems of estimated reductions in CSO volumes is clearly limited. Given the specific nature of each drainage network, an

evaluation of the RTC potential for a given system can be achieved only after a thorough evaluation based on calibrated models with different levels of complexity (as outlined in e.g. the M180 guidelines, Schütze et al. 2008). Nevertheless, the benchmarking performed in this study clearly shows the improved performance obtained by DORA in comparison with traditional approaches.

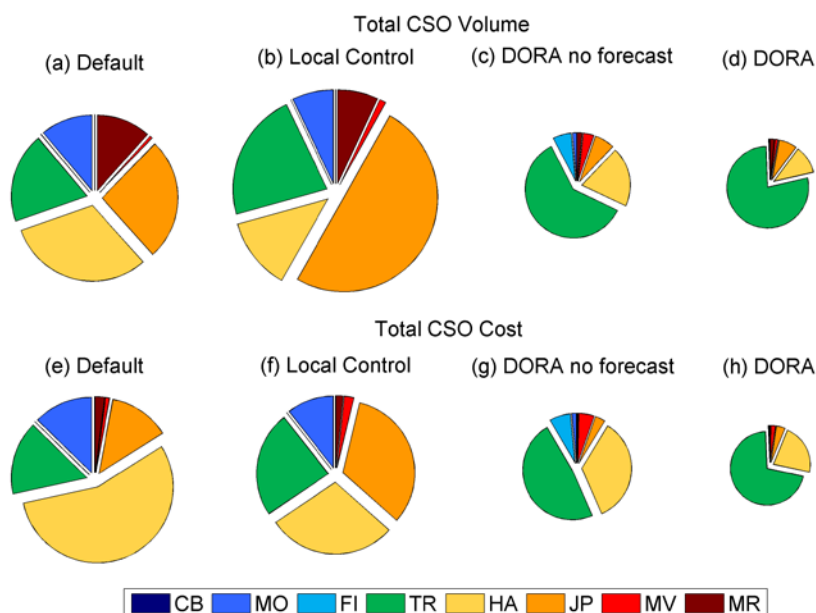


Figure 8. Distribution of CSO volume (a-d) and CSO cost (e-h) among the different CSO structures for the four simulated scenarios.

3.2. Local Sensitivity Analysis

3.2.1. Influence of overflow cost scale

The influence of the cost scale on the performance of DORA can be seen in Figure 9. When looking at the total overflow volume (last bars in Figure 9a), the choice of the cost scale did not lead to significant changes: the coefficient of variation (COV – the ratio between standard deviation and mean value) is in fact 0.02. Similar results were obtained when looking at the individual overflow events (Figure 9b): the variation of the overflow volume was limited, with COV ranging from 0.02 to 0.76 (with higher COV values for small overflow events). Conversely, the different cost scale affected CSO volume discharged by individual overflow structures (Figure 9a): this can be seen clearly by looking at

the CSO volume from the north-eastern part of the system (basins Troejborg – TR – and Havnen – HA). Also, major differences were observed for medium events (i.e. with T_r lower than 0.5 years – Figure 9b), i.e. for those events whose rainfall volume was comparable to available storage capacity (i.e. where RTC potential is greater).

The effect of the cost scale on the optimal settings identified by DORA can be observed in the filling degrees for different basins (e.g. Figure 10). When all the basins have similar importance (equal cost), HA and TR are filled at a similar rate (e.g. the two basins reach a 100% fill at the same time, as seen in Figure 10b). This results in a greater CSO volume from HA compared to other cost scales. When the spread of the CSO costs between the two basins increases (i.e. with the linear and the exponential cost scale), TR tends to be filled earlier than HA (as can be seen from the delayed filling of HA compared to TR in Figures 10d and e), in order to reduce overflow risk in the latter. The direct consequence is an increase in CSO volume at TR and a consequent reduction in the most sensitive HA basin (and a reduction in total CSO cost discharged from the two basins).

These results show how the choice of how one prioritises overflow structures (obtained by assigning different CSO costs c_i) does not affect the overall performance of DORA, as DORA succeeded in achieving important reductions in CSO volumes irrespective of the chosen cost scale. Additional investigations (not shown here) confirmed this pattern, showing that DORA's performance is not dependent on the absolute value of c_i , but rather on the spread between basins and the chosen CSO prioritisation. In fact, the optimal solution found by the genetic algorithm is limited by the physical characteristics of the system (i.e. the minimum and maximum flows allowed for each connection), which appeared to be more important for the final results than for CSO costs c_i . For example, the optimal flow between TR and HA (and thus their filling degree and, consequently, CSO volume) is affected strongly by the ratio of the adopted costs. When the ratio is 1:1, DORA modifies the outflow from TR in order to fill the basins at an equal rate. When the ratio is increased to 1:10, DORA closes the TR-HA connection in order to protect the downstream basin, which is smaller and more sensitive (i.e. it has a higher CSO risk). Increasing the ratio to 1:100 would not result in a different control strategy, as the chosen control (closing TR-HA) would be the same as for the 1:10 scenario. Similarly,

the characteristics of HA (highly sensitive and with limited storage capacity) will result in the majority of cases fully exploiting the capacity of the HA-FI connection, i.e. the optimal flow from JP corresponds to the maximum flow for all the scenarios.

Furthermore, the analysed model outputs (number of CSO events and CSO volume) are non-linear: if a CSO is avoided for $c_i=10$, it will be avoided also for $c_i=100$, resulting in apparent non-sensitivity to the value of c_i . However, when looking at other model outputs, such as filling degree (as in Figure 10), the influence of CSO cost might be easier to assess.

These results suggest that the absolute value of c_i should not be the object of calibration, but it should be defined by urban water managers who should reflect the relative importance of each point (i.e. they should answer the question “How important is basin X compared to basin Y?”).

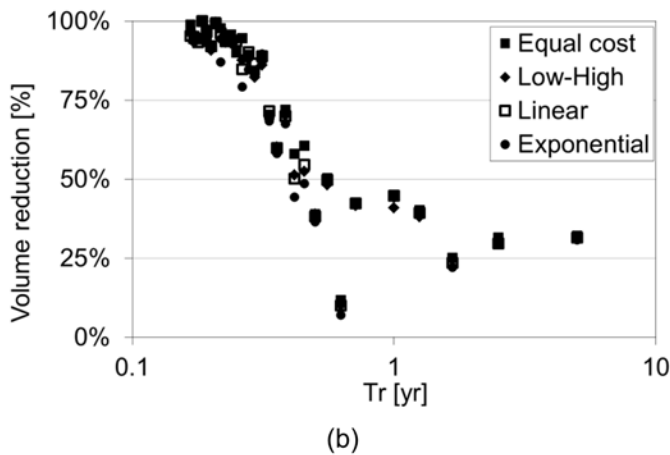
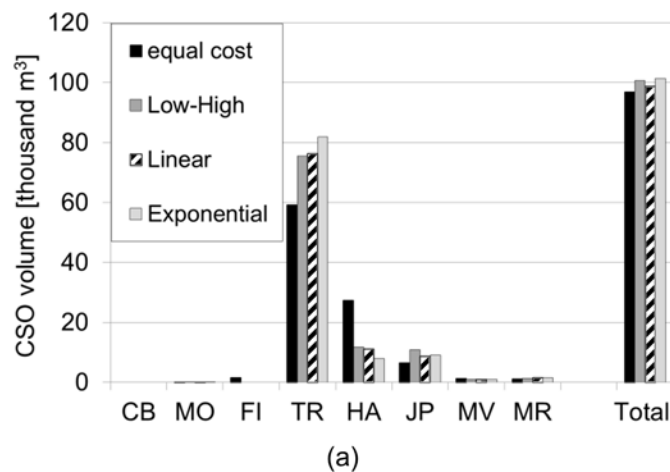


Figure 9. (a) Sum of CSO overflow volumes for all the discharge points with different scales for overflow costs c_i , and (b) reduction of total CSO volume (sum over all the CSO structures – y-axis) for individual events against their estimated return period (x-axis)

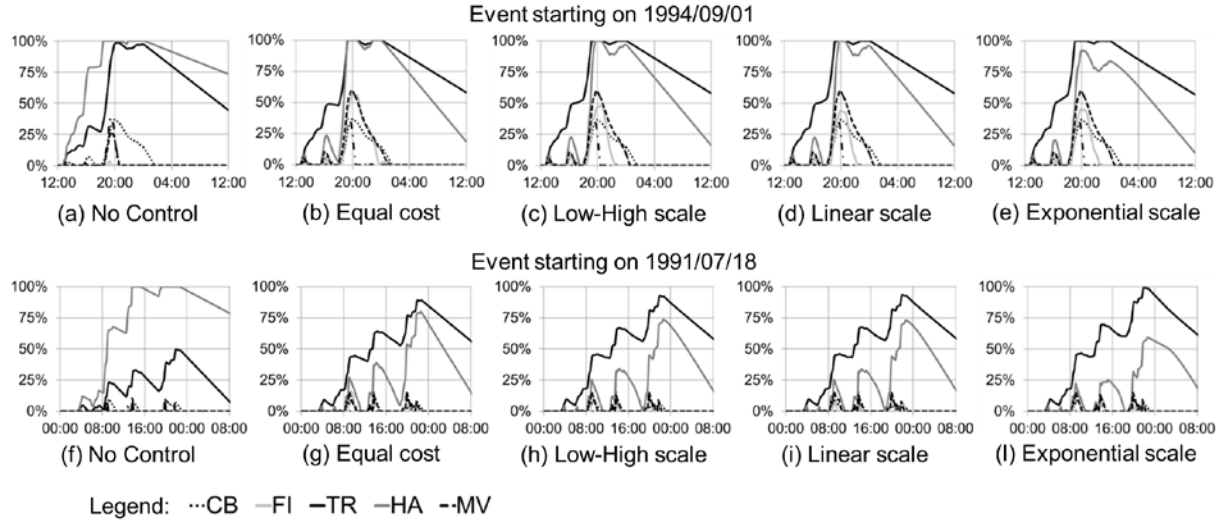


Figure 10. Filling degree in selected basins for two rain events (MO, JP and MR are neglected for reasons of clarity).

3.2.2. Influence of discount function

When varying the value of k_{hor} , total CSO volume reduction compared to the baseline scenario for the 30 largest overflow events ranged between 53.8% and 54.5%. Major variations in performance were observed for minor overflow events caused by several close rain events (the events shown in Figure 10), when the first events had already used a great proportion of the available storage volume.

The influence of parameter α (which is a safety factor added to avoid the accumulation of wastewater due to an incorrect estimation of the volume expected from the upstream basins) on the performance of DORA is shown in Figure 11. The total reduction in overflow volume ranged between a maximum of 54.5% and a minimum of 50.5%, a variation which was caused almost entirely by the discharge at the Jaergergaards-gade pumping station (JP). In fact, given the small storage volume (100m^3) and the

great flows from upstream basins (up to 1.3 m³/s), high α values interfered with the optimal emptying of this basin.

The local sensitivity analysis showed that the discount function (Eq. 8) had a minor influence on the performance of DORA. These results depend highly on specific network characteristics, as well as the characteristics of rain events causing the overflows. Therefore, it does not seem possible to suggest default values for the three parameters of the discount function, which need to be estimated on a case-by-case basis using a large number of overflow events. Nevertheless, tuning these parameters only has a minor influence (a few per cent) compared to the overall benefit of applying DORA (up to an average of 54% for the simulated case).

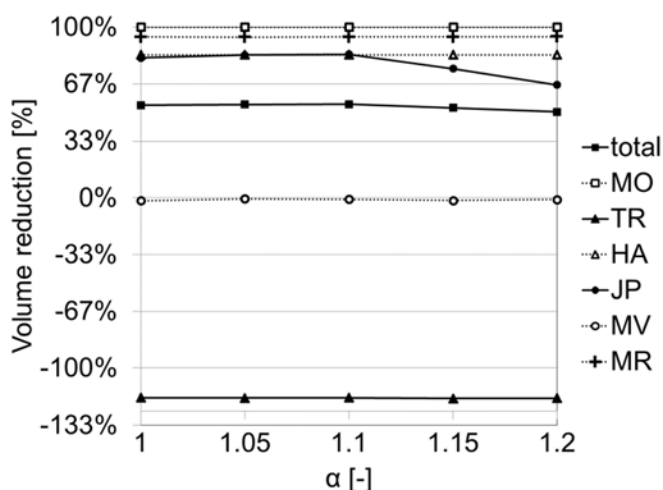


Figure 11. Reduction in overflow volume of the 30 biggest CSO events for different α values.

3.3. Future outlook

DORA is currently being implemented in three large Danish urban catchments: one in the city of Aarhus, one in the city centre of Copenhagen and one in the western suburbs of Copenhagen (see Grum et al. 2011 and Vezzaro et al. 2012). In all of these case studies, DORA has been coupled to a detailed deterministic hydraulic model (MikeUrban – www.mikebydhi.com), which provides a more detailed representation of the situation in the system than the simple conceptual model used in this study. In addition, runoff predictions are obtained by using radar observations (Thorndahl et al., 2013),

which provide a more accurate representation of the spatial distribution of rainfall. These three implementations represent an important source of information for testing and assessing the performance of DORA during full-scale operation. In the future these catchments will be controlled by a full MPC approach (covering various parts of urban drainage systems, ranging from radar-based forecast models to WWTP models), representing a key reference point allowing for the wider application of these tools.

Uncertainty in runoff predictions beyond the forecast horizon T_{hor} (currently defined at 2 hours) can be quantified by using weather model predictions based on, for example, ensemble forecast models (as introduced by Courdent et al., 2014). Moreover, by analysing historical measurement series, it is possible to estimate the bimodal conditional probability density function of the amount of runoff that can be expected in any X-hour period in the future (e.g. T_{cr} to 12 hours), given the observed and forecasted runoff to this point. This would further improve the performance of the system when dealing with events beyond the current capability of nowcasting models. Additionally, the assumptions of constant flows between controlled nodes and T_{cr} calculated across the entire catchment (Section 2.1.) could be revised in order to further improve the performance of DORA.

Current research is now focusing on the application of stochastic models (such as those presented by Breinholt et al., 2011 and Löwe et al., 2013) for runoff estimation (Vezzaro et al., 2013). This will provide a more accurate and dynamic estimation of the uncertainty affecting runoff volume, thus affecting the estimation of overflow risk.

The flexibility of the DORA cost function helps in considering additional factors. The control strategy can aim to minimise, for example, pollution loads discharged by overflow structures, integrating the approach presented by Lacour and Scheutze (2011), Hoppe et al. (2011) and Gaborit et al. (2012). While these examples are currently applied at a local scale and/or are based on rule-based controls, DORA will enhance these approaches to a global and integrated level. A preliminary study showing the potential of DORA in a water quality-based control strategy has been presented by Vezzaro et al. (in press).

Other factors that are currently investigated are energy consumption due to pumping operation (and its connection to energy prices and smart grids), the risk of sludge loss in the secondary clarifier due to hydraulic an overload of the WWTP and the risk of pluvial flooding. Therefore, DORA can represent the central element in the potential development of multi-control strategies.

4. Conclusion

A generalised global approach to controlling urban drainage systems was presented in this study, in order to improve the performance of urban drainage systems. By integrating the information provided by runoff forecasts with a Dynamic Overflow Risk Assessment (DORA), existing storage capacity can be better exploited, while the different sensitivities of receiving waters can be taken into account. The simulations performed by using a simplified hydrological model to represent a catchment in Aarhus showed that (i) the global approach generally performed better than the traditional local RTC approach, which requires greater effort to tune than DORA; (ii) available storage capacity in the system was better exploited; (iii) the inclusion of runoff predictions, together with the related uncertainty, led to better performance for medium-big CSO events ($T_r > 0.5$ yr); (iv) the scale chosen to prioritise overflow structures allows for the protection of more sensitive discharge points and (v) the sensitivity of the parameters (estimated over 30 rain events with different magnitude) was low, ensuring robust control strategy performance. The method presented in this study thus represents an important starting point towards a wider and more robust application of model-based urban drainage system control, including the use of various objective functions.

5. Acknowledgments

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