A generalized Dynamic Overflow Risk Assessment (DORA) for urban drainage RTC

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ABSTRACT

An innovative generalized approach for integrated real time control of urban drainage systems is presented. The Dynamic Overflow Risk Assessment (DORA) strategy tries to minimize the expected overflow risk by considering (i) the water volume presently stored in the drainage network, (ii) the expected runoff volume (calculated by radar-based rainfall forecast models) and (iii) the estimated uncertainty of the runoff forecasts. The inclusion of uncertainty allows a more confident use of Real Time Control (RTC). Overflow risk is calculated by a flexible function which allows prioritization of the discharge points according to their sensitivity. DORA was tested on an example inspired by a catchment in the city of Aarhus (Denmark). By using a simple conceptual model, a statistical analysis of the performance of DORA was performed. Compared to a traditional local control approach, DORA contributed to reduce Combined Sewer Overflow loads and to optimize the flow discharged to the wastewater treatment plant. Also, the inclusion of forecasts and their uncertainty contributed to further improve the performance of drainage systems. The results of this paper will contribute to a wider usage of global RTC methods in the management of urban drainage networks.

KEYWORDS

Integrated urban water management, Model Predictive Control, Overflow risk, Real Time Control, Uncertainty

1 INTRODUCTION

Real Time Control (RTC) of urban drainage systems is increasingly applied to improve the performance of existing drainage networks (as shown in the examples presented by Muschalla et al. (2009); Puig et al. (2009), de Korte (2010); Schutze and Haas (2010)). In fact, RTC can contribute to better exploit the available storage capacity (reducing the risk of Combined Sewer Overflows (CSO) and pluvial flooding) and to improve the management of WasteWater Treatment Plants (WWTP) during wet weather conditions. RTC represents a flexible and cost-effective tool which can help urban water managers to meet the stricter environmental regulatory requirements, to fulfil the increasing demand for a higher level of service from the population, and to 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 can be seen as a tool that can be integrated with structural solutions rather than an alternative to them, decreasing the total investment that urban water managers (usually public subjects) need to achieve their targets.

RTC can also benefit from information regarding the future evolution of the system based on the result provided by different models (this approach is also known as Model Predictive Control - MPC). Examples of models that can be applied for MPC of urban drainage systems are radar-based rainfall forecast models, hydrodynamic models nowcasting flow in the drainage network, and models estimating the maximum allowed flow through the secondary clarifier in the WWTP. Urban drainage models are affected by several sources of uncertainty (see the analysis in Deletic et al. (2012)) and this limits their full-scale application for MPC to few examples (e.g. Puig et al. (2009), Fradet et al. (2011)). Achleitner et al. (2009) presented an example of integration between a radar-based rainfall model and hydraulic model and underlined the impact that uncertainty in the rainfall model had on the overall performance of the model.

The inclusion of model uncertainty in decision making processes has been applied at a larger scale than urban areas. Coccia and Todini (2011), for example, illustrate examples where uncertainty in river flow predictions can be integrated into a flood warning system. In urban system, 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 considered when controlling the system in real time.

This article introduces the Dynamic Overflow Risk Assessment (DORA) approach, which was developed to include uncertainty in MPC of urban drainage systems. DORA is a global control strategy which considers the estimated uncertainty in urban runoff predictions and utilizes this information to reduce the expected overflow costs in the entire catchment. The potential of DORA to contribute to CSO reduction is compared against traditional local control strategies in a simplified catchment inspired by a real system. The theoretical results presented in this study provide the background for a 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 optimization strategy which uses a simplified representation of urban drainage networks. Only storage units that are included in the control strategy are taken into account, while travel times between the nodes of the network are neglected in this first version of DORA. A cost is associated to each node of the network, which reflects the sensitivity of the receiving water body to CSO discharge (see section 2.2.1).

Each *i-th* detention basin of volume V_B [m^3] can be schematized as described in Figure 1a. The inflow to the basin is represented by the sum of the flow from the upstream basins (lumped into Q_{in} [m^3/s]) and Q_F [m3/s], which is the runoff generated in the *i-th* sub-catchment (of area A_i [m^2]) that is directly connected to the basin. The latter is calculated by a simple rainfall-runoff model based on the measured and forecasted rainfall.

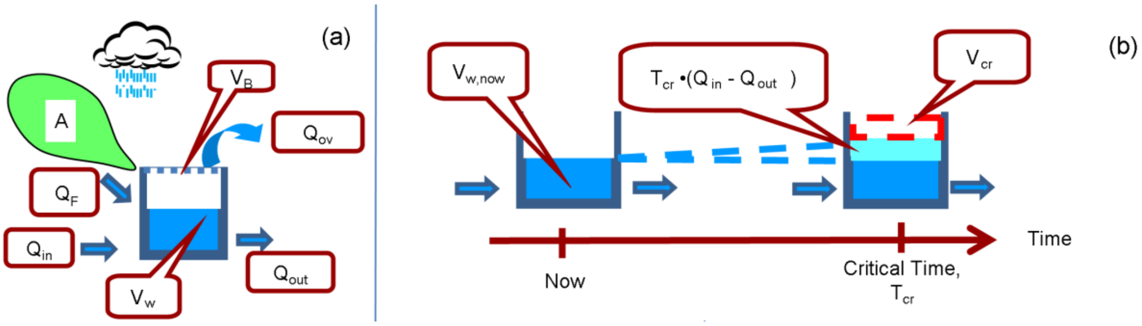

Figure 1. (a) Schematic diagram of a detention basin; (b) representation of the critical volume V_{Cr}.

The outflow Q_{out} [m^3/s] can be fixed (as in the case of the connection to the wastewater treatment plant) or can be regulated by the control strategy. When the total inflow to the basin exceeds the outflow capacity Q_{out}, runoff is stored in the basin until the storage capacity is filled and the exceeding flow Q_{OV} [m^3/s] is discharged by the overflow structure.

The RTC strategy operates within the critical time T_{cr} [s], which is defined as the time interval required by the forecasted runoff in the entire catchment to fill the available storage volume in the entire system. This can be expressed in mathematical terms as:

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

i.e. T_{cr} mark the instant when all the runoff forecasted in the subcatchments equals the total storage volume, and the RTC strategy has no more capacity to avoid overflow. The critical volume V_{cr} [m^3] is defined as (Figure 1b):

$$V_{cr} = V_B - V_{w,now} - \int_{now}^{T_{cr}} \left(Q_{in}(t) - Q_{out}(t)\right)dt \tag{2}$$

where $V_{w,now}$ [m^3] is the volume of water currently stored in the basin, and the last term of eq. 2 represents the variation in the water volume until T_{cr}. When T_{cr} is greater than the forecast time horizon T_{hor} [s] (defined as the time threshold when the uncertainty in runoff predictions becomes too great for practical application), T_{cr} is substituted by T_{hor} in eq. 2. This limits the influence of forecast on the control only to the time interval when those are reliable. Assuming that Q_{in} and Q_{out} are constant (i.e. when the system is not controlled and flow between nodes is not changing), eq. 2 can be rewritten as:

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

2.2 Dynamic Overflow Risk Assessment

2.2.1 DORA global cost function

The DORA strategy aims to minimize the overall cost due to overflow events in the catchment. This is calculated as the sum of the overflow costs occurring in each *i-th* basin of the catchment, which can be subdivided in three terms.

$$Cost = \sum_{i=1}^{N_{basins}} \left(C_{cr,i} + C_{F,i} - C_{hor,i}\right) \tag{4}$$

where the first term ($C_{cr,i}$) is the cost due to overflows generated by the runoff volume that already entered the drainage network, the second term ($C_{F,i}$) expresses the cost due to expected runoff events in the time interval defined by the *forecast horizon* and the third term is a factor which tries to maximize the available storage volume beyond the forecast horizon T_{hor}. A detailed description of the terms is presented in the following sections.

2.2.2 Overflow cost

The first term in eq. 4 is associated with overflows caused by the current flows in the system (i.e. water which is already stored): here the information used by DORA resembles the one employed by traditional RTC approaches. When the water volume discharged from the upstream network (the last term in eq. 2) exceeds the available storage volume, the critical volume V_{cr} is negative and corresponds to the overflow volume. The cost $C_{cr,i}$ is thus calculated as:

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

where c_i is unitary overflow cost [€/m3].

2.2.3 Cost of forecasted runoff

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

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

The various sources of uncertainty affecting runoff predictions affect the estimation of the runoff volume V_F (as illustrated in Figure 2a): different runoff predictions can lead to different values of V_F, with an associated probability value $p(V_{F,i})$. 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). The overflow risk is then estimated by using the formula also applied in Coccia and Todini (2011):

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

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 weather forecast models.

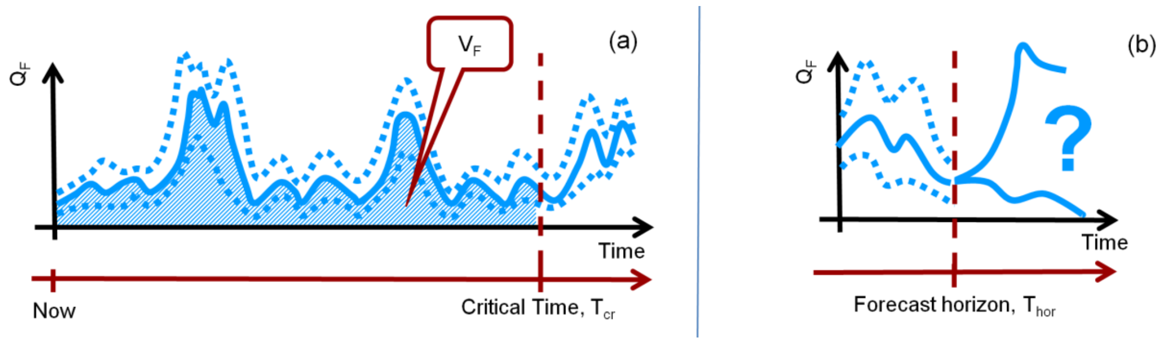

Figure 2. (a) Schematic representation of forecasted runoff volume V_F (hatched area) and respective uncertainty bounds; (b) possible development of runoff beyond the forecast horizon $T_{hor.}$

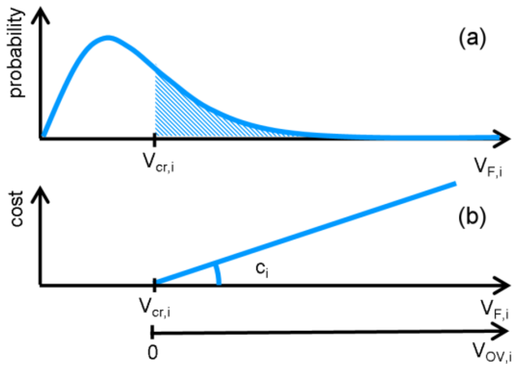

Figure 3. (a) Probability distribution of forecasted runoff volume V_F , where the hatched area represents the total probability of the overflow, and (b) the associated overflow cost function, as used in eq. 7.

Although the integral in eq. 7 can be solved by using numerical methods, a gamma distribution is used in this study to represent uncertainty in the forecasted runoff volume. This rough assumption allows solving eq. 7 analytically.

2.2.4 Discount function

The overflow risk considered by eq. 7 is based on the known level of uncertainty of runoff predictions. Runoff forecast beyond the *forecast horizon* T_{hor} are affected by such level of uncertainty that cannot be used for practical applications (Figure 2b). According to the terminology proposed by Walker et al. (2003) and further developed by Warmink et al. (2010), the *forecast horizon* thus represents the limit of the *qualitative uncertainty*, as uncertainty beyond T_{hor} can be described but cannot be quantified. DORA accounts for this ignorance by using the discount factor $C_{hor,i}$ in eq. 4.. The discount is in the order of magnitude of 10^{-5}, i.e. it plays a role in the system optimization only when basins are almost empty and the overflow risk is low. For example, when only dry weather flow is present, the overflow risk (calculated by eq. 7) is low (around 10^{-9}-10^{-10}), the genetic algorithm may become unstable and lead to sub-optimal solutions. The optimal configuration is thus identified thanks to $C_{hor,i}$, which privileges empty basins, with a greater outlet capacity at the most sensitive basins. Whenever a new rain event appears within the time horizon defined by T_{hor}, the overflow risks grows and the influence of $C_{hor,i}$ becomes negligible. The use of the discount factor resembles a traditional global RTC approach, as it assigns a lower cost to the control settings ensuring a faster emptying of basins. This ensures that the catchment can cope with unforeseen large rain events beyond the forecast horizon.

2.3 Evaluation of DORA performance

2.3.1 Simplified Marselisborg catchment

The performance of the DORA control strategy was evaluates on a theoretical example inspired by the Marselisborg catchment (Figure 4), located in the city centre of Aarhus (Denmark). The total reduced area is about 280 ha, subdivided into eight catchments with different size (Table 1). The runoff from these catchments (Q_F) is calculated by using a time-area method and the concentration time listed in Table 1. The total storage capacity in the system is about 43200 m^3, subdivided into six detention basin and two pumping station with limited storage volume (JP and MR - Figure 4).

The Carl Blocks Gade subcatchment (CB) discharges to 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.

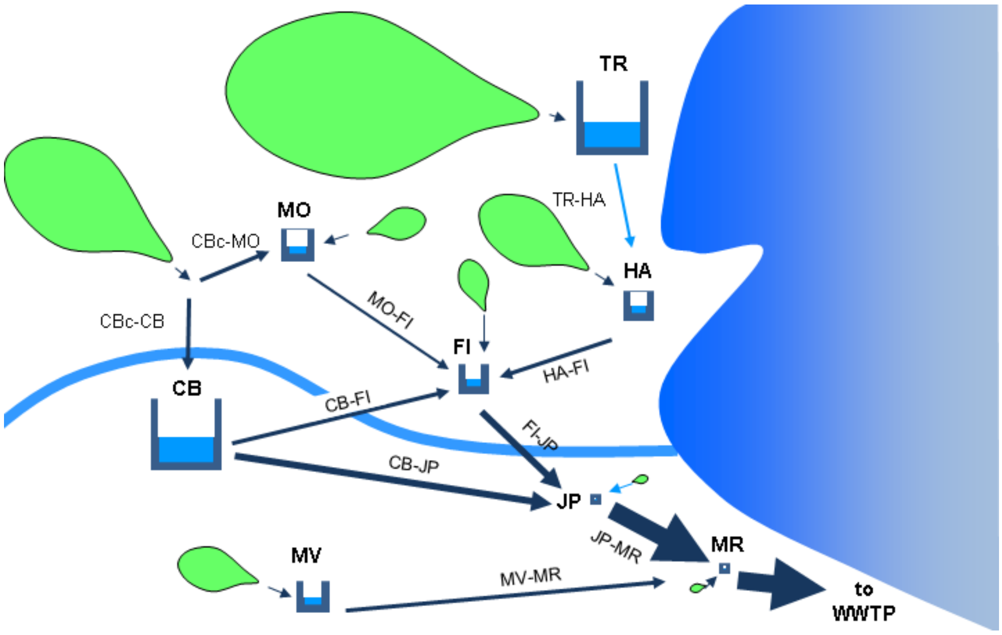

Figure 4. Scheme of the simplified Marselisborg catchment.

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

Subcatchment	Red. Area [Ha]	Concentration time [s]	Basin Volume (V_B) [m3]	Dry weather flow [l/s]	CSO Price [EUR/m3]	Downstream connection	
						Length [m]	Max Q_{out} [m^3/s]
Carl Blocks Gade (CB)	64	900	15200	64.5	2,8	760[a] 1720[b] 2120[c]	0.65[a] 0.40[b] 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 catchment discharges to the Marselisborg WWTP, which has a capacity of 200,000 PE and a maximum flow of 1.4 m^3/s. 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. The basins' overflow structures discharge in the Aarhus Stream or in the Aarhus harbour: different costs are thus assigned to the each overflow structure according to the vulnerability of the recipient (Table 1).

The Marselisborg catchment was simulated by using the WaterAspectst™ conceptual model (Grum et al., 2004), and 5-year rainfall data (from 1991 to 1995) were retrieved from the Viby J. wastewater treatment plant station, 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 uncertainty represented by the gamma distribution) uniformly distributed across the catchment. A genetic algorithm was used to minimize the expected overflow costs. Overflow events were identified by running the model with the 5-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 after at least 8 hours from the previous event. Due to this definition, a single overflow event can include several rain events of different magnitude. Also, the frequency of the overflow event does not necessarily correspond to the frequency of the rain event(s) which generated it.

2.3.2 Comparison of RTC approaches

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

1. *Baseline*: drainage network without any control of flows
2. *Traditional local RTC approach*: a local control is applied to reduce the difference $\Delta\theta$ between the filling degree of the basins (this "Equal Filling Degree" strategy is widely applied - see among others Borsanyi et al. (2008) and Dirckx et al. (2011)). To account for the different sensitivity of the basins (expressed through the unitary costs c_{up} and c_{down}), the control minimized $\Delta\theta^*$, which for two basins is defined as:

$$\Delta\theta^* = \theta_{up}^{\frac{c_{up}+c_{down}}{2c_{up}}} - \theta_{down}^{\frac{c_{up}+c_{down}}{c_{down}}} \tag{8}$$

   where θ_{up} and θ_{down} are the filling degrees of the upstream and downstream basin, respectively. This formulation privileges lower filling and faster emptying of the more sensitive basins

3. *DORA without forecast*: the drainage network is optimized by only using information regarding the dry weather flow and the present water volumes.
4. *DORA*: the proposed control strategy is applied by including runoff forecasts in the optimization of the system.

3 RESULTS AND DISCUSSION

3.1.1 Comparison of RTC approaches

The simulated overflow volumes and the associated costs for the 25 bigger CSO events (i.e. with a return period T_r from 5 to 0.2 years) are shown in Figure 5. Generally, all the simulated controls succeeded in reducing the overflow volume and costs from the most sensitive outlet (e.g. overflow in HA are reduced by 50-60% on average by all the approaches). Figure 5c,d show how the performance of all the control methods were strongly dependant on the characteristics of the rain event: as expected, better results were obtained for more frequent (and thus smaller) rain events. However, strong variability is noticed between overflow events of similar magnitude, which can fill the basins in different ways (e.g. a single rain event and multiple rain events can generate similar overflow volumes, but the latter allow better degree of freedom for control). This result stress the importance of a statistical analysis based on long-term time series when assessing the performance of RTC approaches. When looking at the traditional local RTC, the total CSO volume was generally increased compared to the baseline scenario (+24% on average), although the total costs were decreased for more frequent events ($T_r < 0.5$). Figure 5d shows that up to 50% reduction in CSO costs are obtained for events with $T_r < 0.33$. The increase in CSO volume was caused by an overloading of the cheap downstream nodes (JP and MR) to protect the upstream sensitive points (e.g. HA), while the capacity of the upstream basins (e.g. TR, CB) was not used. This emphasizes the need for a global control strategy which tries to exploit the available upstream storage capacity.

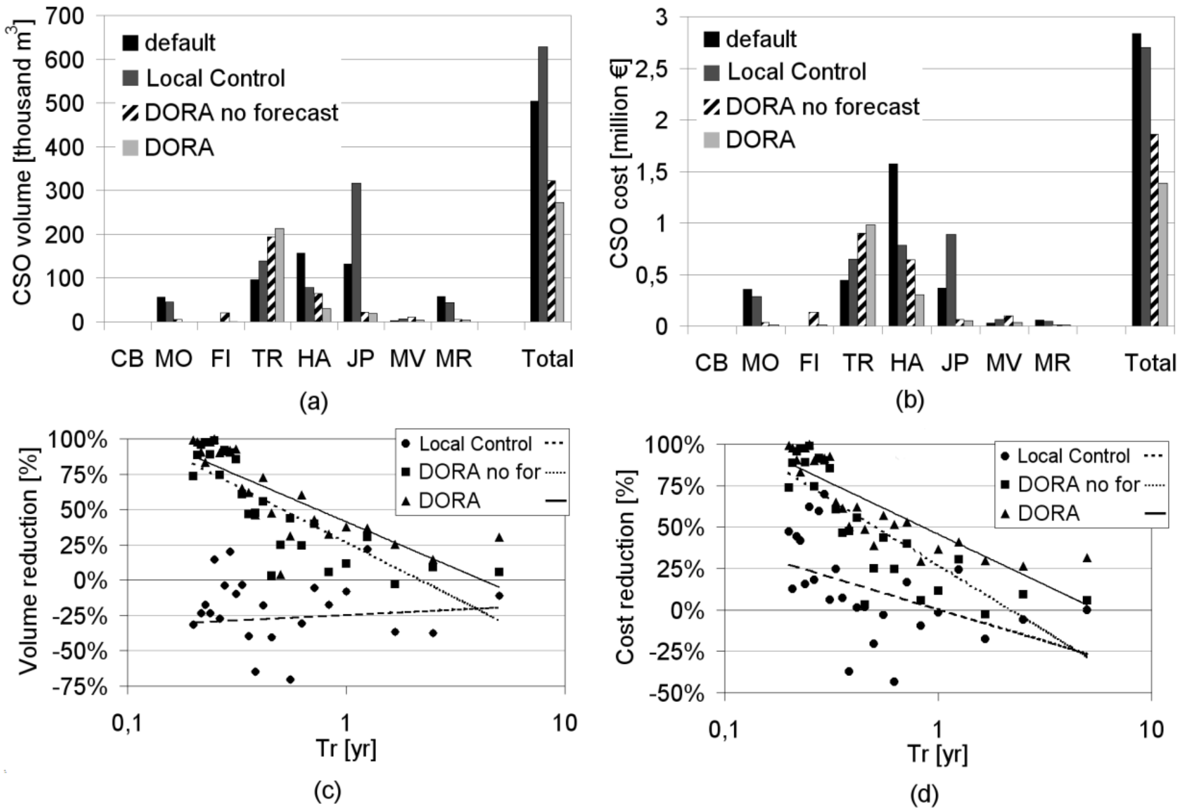

Figure 5. Results of the simulated for the 25 bigger CSO events in the period 1991-95: (a) total overflow volumes, (b) total CSO costs, (c) event performance for CSO volume, and (d) event performance for the CSO costs.

It is important to stress that the traditional RTC approach can be further optimized by improving the control rules in the 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 is however time demanding and it represents an important drawback compared to fast implementation required by DORA.

DORA achieved a reduction in both CSO volumes and costs both without and with runoff forecasts. This was obtained not only by reducing the CSO in the sensitive areas (up to 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 showed 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.

The benefit of including runoff forecasts and the related uncertainty in the estimation of the volume is exemplified by the trend lines in Figure 5c,d: a greater reduction in CSO volume and costs is in fact achieved in the last scenario. DORA without forecast tended to protect downstream basins (e.g. JP) by storing water in the directly upstream basins (e.g. FI): in this case DORA resemble a traditional local RTC approach, as emptying of basins is solely controlled by filling degrees. Nevertheless, the global approach ensures a greater reduction of CSO impact than local RTC. The addition of forecasts resulted in an increased exploitation of the storage capacity in the upstream part of the catchment (mainly TR and CB). In this case DORA controlled also the filling of the basins, as – to protect downstream and more expensive basins – upstream basins started to fill earlier compared to the scenario without forecast. Forecasts provided better improvements for medium-big events, while in some limited cases CSO was increased when using forecasts. This was observed for a limited number of small events with peculiar characteristics. In those cases, for example, the storage in upstream basins was reaching 90-95% filling without forecast, while with forecasts the maximum storage was exceeded to protect the downstream basins. However, these few episodes did not affect the overall results, as the use of forecasts resulted in a 13% greater reduction of CSO costs (compared to the baseline scenario) than DORA without forecasts.

3.1.2 Future outlook

DORA is under implementation in two Danish urban catchments in the city centre of Aarhus and Copenhagen (see Grum et al. (2011)). In both these case studies DORA is coupled with 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. Also, runoff predictions are obtained by using radar observations, providing a more accurate representation of spatial distribution of rainfall. These two full-scale implementations represent an important source of information for testing and assessing the performance of DORA when operating full-scale. In the future these catchments will be controlled by a full MPC approach (covering the various part of urban drainage systems, ranging from radar based forecast models to WWTP models) representing a key example to ensure a wider application of these tools.

Also, in this study only overflow volumes are considered. The flexibility of the DORA cost function allows considering additional factors. The control strategy can aim to minimize, for example, the pollution loads discharged by overflow structures, the energy consumption due to pumping operation, the risk of sludge loss in the secondary clarifier due to hydraulic overload of the WWTP, the risk of pluvial flooding. Therefore, DORA can represent the central element in the potential development of multi-criteria control strategies.

4 CONCLUSION

A generalized global approach for control of 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 Analysis (DORA) the existing storage capacity is better exploited and the different sensitivity of the receiving waters is 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 a traditional local RTC approach, which requires greater efforts to be tuned than DORA; (ii) the available storage capacity in the system was better exploited; and (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). The method presented in this study thus represents an important starting point towards a wider and more reliable application of model-based control of urban drainage systems, including the use of various objective functions.

5 ACKNOLEDGMENTS

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