Is flow control in a space-constrained drainage network effective? A performance assessment for combined sewer overflow reduction

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A B S T R A C T

Recurring combined sewer overflows (CSOs) can have a significant impact on the ecological condition of receiving water bodies. There are several structural measures, like adding retention basins and switching to low impact development solutions, that have been proposed to reduce the number of sewage overflows. Besides, several flow control strategies have been discussed in scientific literature that take advantage of the space within urban drainage networks, which is assumed to be adequate, for temporary storage. The adequacy of such storage space, however, is not a universally valid assumption as a large fraction of drainage networks frequently operate close to their design discharge. In this paper, we investigate the efficacy of flow control for a space-constrained drainage network. We employ a low-cost, heuristic real time control strategy with the use of flow control devices (FCDs) and available in-sewer space to reduce the magnitude of CSOs. We consider the performance of the proposed control strategy and discuss the effect of FCD location on CSO reduction. Our results, based on over 300 rainfall-event simulations, show that the flow control strategy using limited sewer capacity is more efficient during relatively small rainfall events, where the CSO is large enough to enable reduction using the chosen control rules. The CSO is reduced, to varying degrees, for around 80% of rainfall events with peak intensity between 10 and 20 mm h\(^{-1}\). For larger rainfall events, the flow control is more unstable in response to abrupt water release during control operation, which seems to be unavoidable because of the water accumulation effect and the transition to pressurized pipe flow in space-constrained networks. We also found that the flow control performance is highly sensitive to the FCD location – as it depends on the interplay of the peak rainfall intensity and the water level condition immediately upstream of the FCD. The efficacy of a location for flow control is determined by the unfilled capacity (i.e., effective in-sewer storage potential) in the pipe upstream of the FCD during the rainfall peak; furthermore, the location also has to be resistant to the water accumulation effect. Using our analysis, we substantiate two anticipated caveats to flow control strategies when the storage space is limited in a drainage network: diminished performance in CSO reduction and the appearance of additional control-related challenges, which are otherwise mitigated in more spacious networks.

1. Introduction

Unmanaged stormwater discharges have become a potential hazard for urban ecosystems, manifesting as pollution spills into surface water bodies. This increasing risk is caused by the expansion of impervious urban surfaces and the limited hydraulic capacity of drainage systems. This problem is exacerbated by the increasing frequency of extreme rainfall events due to climate change. During intensive rainfall events, excess stormwater may cause not only urban flooding but also an increase of system discharges, creating a threat to local environment (U.S. EPA, 1994; Lund et al., 2014; Crocetti et al., 2020). Combined sewer overflows (CSOs) occur when the hydraulic capacity of the urban drainage system, namely drainage components, such as sewer pipes and pumps, and the wastewater treatment plant (WWTP), is exceeded. Increased frequency of CSOs calls for better management of sewer systems especially during wet weather. For example, Cembrano et al. (2004) and Cunha et al. (2016) propose optimal control techniques to solve flooding and CSOs challenges based on storing water volume in detention tanks. Joshi et al. (2020) compare and analyze four sustainable urban drainage system techniques (bioretention cell, permeable...
pavement, rain barrel and green roof) and their spatial deployment strategies to reduce CSOs. Other stormwater management infrastructures, such as infiltration basins, retention units, urban green infrastructures, can also be implemented to improve stormwater management in cities (Zolch et al., 2017). The construction and upgrade of these infrastructures usually require large dedicated areas and financial investments. To circumvent these challenges, the CENTAUR project aimed at reducing flood risk with innovative data driven in-sewer flow control system, utilizing the spare capacity of drainage networks (Leitão et al., 2018; Eulogi et al., 2020). The installation of flow control devices, such as CENTAUR, allows for the usage of any free storage capacity in existing sewer networks, which can also have a positive impact in reducing CSOs.

The dynamic modelling of integrated urban drainage system first emerged in the 1970s (Gujer et al., 1982; Bach et al., 2014). It was followed by integrated real time control (RTC), which focused on the dynamic process and interaction among system components. García et al. (2015) reviewed the main modelling and RTC techniques that have been applied to urban drainage systems, focusing on RTC strategies classification, modelling approaches and software tools. Historically, reduction of the discharge to the receiving water body at the main drainage network outlet with smart controls of the flow in the system has shown to be an efficient solution to reduce and/or delay runoff volume and allow the reduction of CSO volumes, despite the complexity and dynamics of urban drainage systems. Borsányi et al. (2008) assessed the performance of RTC strategies under different climatic conditions using two hypothetical sewer systems. Montestruque and Lemmon (2015) described a highly-distributed wireless cyber physical system (CPS) called CSOnet controlling sensors and actuators embedded in the sewers to reduce overflow volume during storm events with the storage and conveyance capacity of the sewer network. Kroll et al. (2018) highlighted for the potential of RTC strategies, showing the automated design of control strategies for combined sewer networks and pointing out that the selection of the flow control locations is critical to the success of an RTC strategy and that this location topic should be further investigated in the future. Mullapudi et al. (2018) studied a “smart” real-time stormwater control system to maintain downstream flow with a hardware stack and a cloud-based controller. Mounce et al. (2020) used a fuzzy logic (FL)-based RTC approach based on genetic algorithm (GA) for optimising the FL membership functions (MFs) to reduce the local flood risk. Using similar algorithm and methods, Li (2020) developed a data-driven toolbox for real-time control optimization-simulation to mitigate downstream flooding, enhancing fuzzy control efficiency and improving controller optimal performance and flooding volume reduction. Recently, with the advances of artificial intelligence applications, deep reinforcement learning has been used to learn real-time control strategies by interacting with the distributed stormwater system (Mullapudi et al., 2020). Their results showed that reinforcement learning methods can control individual sites efficiently while the performance is sensitive to the formulation of the deep neural network. RTC retrofit of existing detention basins was also investigated by Schmitt et al. (2020). They tested two RTC algorithms using design storms of varying magnitudes and a 15-year time series dataset, emphasizing on the importance of evaluating RTC measures under a wide range of precipitation conditions.

While applying RTC for simultaneously mitigating pluvial floods and reducing CSOs have been discussed, e.g., Beeneken et al. (2013), Vezzaro and Grum (2014), the number of studies on the possibility of CSO reduction using available in-sewer storage and not considering extra storage infrastructure is limited. Garofalo et al. (2017) used a gossip algorithm-based and decentralized real-time system to reduce flooding and CSO. However, their system requires a large number of sensors and automatically movable gates located at every joint node where sub-networks are connected to the main channel. Eulogi et al. (2020) discussed the selection of multiple flow control locations based on hydraulic analysis over a few design storm events. They proposed a genetic algorithm based optimization framework to identify flow control locations but the rainfall characteristics have not been fully investigated. In general, there is still a limited number of studies on the spatial layout of control locations and on the manageable range of rainfall intensities.

This paper presents a detailed analysis on the efficacy of CSO-reducing flow control in the case of drainage networks without additional storage. We operate under the boundary condition that the flow control should not cause any extra flooding. The dependence of results on the FCD location is also discussed. As Lund et al. (2018) presented in the review paper on smart real-time water management based on model predictive control (MPC), few studies have evaluated performance based on long time series, i.e., over a year. Their study also shows that there is higher potential for CSO reduction when relatively small to medium-sized events are considered. We analyze and comment on the control strategies based on long rainfall time series over 30 years, considering small to large rainfall events. By using a large number of rainfall events, we could investigate on whether events with similar rainfall intensities can produce different CSO reduction results. In summary, the novelty of this paper is in the following three main aspects:

a. To assess the performance of flow control to reduce CSO in space-constrained drainage network systems;

b. To investigate the effect of FCD location on CSO reduction, and

c. To discuss control-related challenges in space-constrained drainage networks.

2. Experimental design

2.1. General overview

The selection of the FCD locations used for our analysis was made a priori based on the previous knowledge of the network; the deciding criteria were the cross-section size of the network elements and the proximity to existing CSOs. Four of the five FCDs were located on the main trunk sewer of the network, and the fifth FCD was located on the largest lateral branch contributing to the main trunk sewer. The objective function is formulated as maximising CSO reduction without causing or increasing flooding in the system. The performance is assessed from temporal and spatial perspectives, i.e., under multiple rainfall events and with different FCD locations. The proposed FCD control rule considers (i) flood alarm, (ii) rainfall characteristics and (iii) water level conditions in the system pipes. Control performance can be sensitive to the FCD operation settings; the impact of these setting values on the control performance is also investigated. To evaluate simulation results with the proposed control strategy, the CSO and flood volumes having FCD in operation are compared to the baseline scenario, i.e., the scenario with no installed FCDs. To see how the control strategy works for CSO reduction, the results are presented, including the temporal changes, at several critical locations in the drainage system. To investigate the effect of rainfall characteristics, the results using rainfall events with different intensities are discussed in detail.

2.2. Flow control in urban drainage networks

In the channelized part of urban drainage systems, flow routing can be described by the Saint Venant equations. These momentum and mass conserving mathematical equations are able to describe and capture nonlinearities of flow within drainage pipes more accurately than other simplified routing models (Gemmbrano et al., 2004; Elliott and Trowse, 2007; Lund et al., 2018; Rossman, 2006). More complex hydraulic phenomena such as backwater effects, flow reversals, pressurized flow and local energy losses are taken into account by these models. Local actuators, such as FCDs, can be used to change the flow dynamically.
and, for example retain water in the pipes, changing flow peaks and ultimately reducing CSO discharges volume. According to the classification of RTC strategies, one common way is to divide RTC as heuristic algorithms and optimization-based algorithms (Vitasovic, 2006; García et al., 2015). In this study, we use a fully distributed hydrodynamic model that includes various FCDs operated using a simple heuristic algorithm and rule-based control strategy. The main reasons for choosing such a model and strategy are:

a. Fully distributed sewer network hydraulic models are able to represent the relevant system features and dynamics well, but are computationally too expensive to incorporate complex RTC algorithms, such as optimization-based ones.

b. The heuristic algorithms are simpler and can easily encode expert judgment for otherwise complex systems.

2.3. Proposed flow control strategy to reduce CSO volume and frequency

Rule-based control (RBC) is one of the simplest and widely used heuristic algorithms. Generally, RBC is formulated as off-line since it conducts a control action according to the current status of the system, using previously defined “if-then” rules. However, if the current or future time step for the system input or status is obtained, RBC makes choices between different control rules quickly and can be considered as RTC. Also compared with other RTC algorithms, RBC shows a higher operational stability as it is based on several fixed setting values (Schmitt et al., 2020). In this study, we adopted RBC taking into account three aspects, i.e., flood conditions, system status and rainfall input. The adopted flowchart describing the control strategy adopted is shown in Fig. 1.

To start with the control, the flood alarm is indicated by control nodes just upstream of the FCD. If the water level at these nodes is higher than the set threshold, the flood alarm is marked as “yes” and the FCD fully opens. The threshold can be defined as a specific percentage (θ) of maximum depth of that node; in this study, the threshold value used is 80%. After this, the system status, reflected by the current water level in the network, is analyzed. A high water level means that there is already a substantial volume of water accumulated in the pipe and the storage capacity is not enough to accommodate more water. Meanwhile, we use the rainfall prediction at the time step ahead of the current time as a proxy of the amount of water that will enter the drainage system. In this study this is obtained from a historical rainfall series, and in such case, rainfall is used as a predicted variable and the forecast time step is the same as time resolution of the rainfall time series (e.g., 10 min in this study) in advance. If a rainfall forecast system is available, it can also be integrated into the control strategy. The percentage of FCD opening is defined according to these conditions, and the FCD will be opened fully again when the rainfall event ends and there is enough capacity at the drainage system upstream the CSO structure. To clarify different conditions for operating different control rules, we simply classify water level as “high” (Hh) and “low” (Lw) and relative rainfall intensity at each time step as “large” (Le) and “small” (Sl), with (α1, α2, α3, α4) as FCD operation settings under different conditions (Table 1). Higher water level in the pipe and larger rainfall correspond to potential large flood, which results in a larger FCD opening. In this way, α1 is the largest and α4 is the smallest. The definition of the status as “large” or “small” rainfall intensity and “high” or “low” water level depends on rainfall characteristics, system scale and decision objectives. Equations (1) and (2) show how the control scenarios in this study were defined, i.e., rainfall intensity and water level.

Table 1

| Rainfall intensity | Water level | FCD operation |
|--------------------|-------------|---------------|
| large (Le)         | high (Hh)   | α1            |
| small (Sl)         | high (Hh)   | α2            |
| large (Le)         | low (Lw)    | α3            |
| small (Sl)         | low (Lw)    | α4            |

Fig. 1. Control flowchart based on flood conditions, system status and rainfall input.
\[ p_i = \begin{cases} \text{Le. if } p_{i+1} \geq 0.5 \times \max \{ p_i \}, i = 1, \ldots, n \\ \text{SI. elsewhere} \end{cases} \]  
(1)

\[ h_i = \begin{cases} \text{HH. if } h_i \geq 0.5 \times \max \{ h_i \}, i = 1, \ldots, n \\ \text{Lw. elsewhere} \end{cases} \]  
(2)

where \( p_i \) and \( h_i \) denote rainfall and water level, respectively, at time step \( t \) and \( t+1 \). \( i \) denotes time step during the entire simulation, \( n \) denotes the last time step of the simulation, and \( p_i \) and \( h_i \) denotes the categorical classification of rainfall and water level at \( t \)-th time step, which gets used in the control algorithm (see Table 1.)

2.4. Sensitivity analysis and performance evaluation

The control strategy parameters, \((\alpha_1, \alpha_2, \alpha_3, \alpha_4)\), are based on rainfall intensity conditions and drainage system’s dynamic status (i.e., water level). To investigate the sensitivity of these parameters to the control, we conducted a variance-based sensitivity analysis, which is often referred as Sobol index (Sobol, 2001). The Sobol Index (SI) of variable \( X \) is defined as in Equation (3).

\[ SI(X) = \text{Var}(E[Y|X]) \]  
(3)

where \( \text{Var} \) is the variance, \( E[f] \) is the mean, \( Y \) is the CSO reduction volume, and \( X \) is the parameter under consideration from the entire parameter space. A higher SI value means higher sensitivity.

To test the sensitivity of control performance on different parameters, we vary the opening percentage value of FCD \((\alpha_1, \alpha_2, \alpha_3, \alpha_4)\) from 0.1 to 0.5 and get corresponding CSO reduction volumes. For each operation parameter, the sensitivity index \( SI(\alpha_i) \) \((i = 1, 2, 3, 4)\) is calculated and compared to see the influence on the control performance. Since the CSO reduction is intended to be made in a constrained system, we need to check if the CSO reduction is accompanied with an increase of flooding. We then define the event with the proposed RTC strategy as a successful case with the consideration of numerical errors (\( R \): CSO reduction, \( F \): flood, \( IF \): increased flood), as follows:

a. **No flood scenario** \((R > 0, F = 0)\): CSO volume get reduced when there is no flood \((\leq 0.05 \text{ m}^3)\) in the network with and without FCD;

b. **No increased flood scenario** \((R > 0, F > 0, IF = 0)\): CSO volume get reduced when there is flood \((> 0.05 \text{ m}^3)\) in the network, and increasing flood with FCD is not more than 5% when compared with the baseline (i.e., no-FCD) case.

Based on the definition of successful cases, we evaluate the control efficiency on a large number of rainfall events, with different peak intensities, at different FCD locations. The evaluation is conducted by comparing CSO volumes with active FCD control with those of the baseline case (i.e., with no FCD control), considering both CSO reduction frequency and volumes. We also discuss the FCD location effect on CSO reduction with respect to pipe filling percentage and effective in-sewer capacity. To understand the flow dynamics and control mechanism, several rainfall events are selected for a detailed analysis of the performance of the proposed FCD control rules; we present flow hydrographs, water level in pipes, CSO volume at different locations, and flood and FCD operation curves.

3. Hydraulic model and rainfall data

3.1. Case study network and model

StormWater Management Model (SWMM) is an open-source software provided by U.S. EPA (Rosman, 2008), which simulates water and pollutant transport in sewer systems. It can be used for event simulation of stormwater runoff and relative control strategies. PySWMM (McDonnell et al., 2020) is a wrapped toolbox for SWMM model simulation in Python environment. In our study, the proposed RBC control is implemented using the PySWMM platform, which also simplifies the process of automatically running hundreds of SWMM simulations.

The simplified network is based on a real network of a small village in Switzerland (Fig. 2). The real network was designed as a mixed drainage system (Blumensaat et al., 2018; Keller, 2016) and is more

![Fig. 2. Network used in the study (344 nodes, 339 links, 194 subcatchments, one storage unit, one pump, three weirs and three outfalls).](image-url)
active control (baseline) and with other model networks that incorporate better than a fully synthetic network, and serves the purpose of this study by allowing relative comparisons between a network with no nodes that were not influencing the flow in the main sewer line.

The first simplification we did was to remove the storage units from the model network was further simplified by removing a few pipes and the model as well as the other drainage associated with these elements, e.g., storage tanks are in place to provide specific storage volume buffer, or mark point to check model and numerical errors induced by the dynamic process and control mechanism is also investigated and discussed.

3.2. Rainfall data

To conduct the analysis using a large number of rainfall events with different characteristics, we identified and extracted 5800 independent rainfall events from 1970 to 2017, separated by an inter-event time of 6 h, following the procedure proposed by Adams and Papa (2001). The rainfall events were classified based on their peak intensities, as shown in Table 3. Since most of the rainfall events fall in the range of small peak intensities (0–10 mm h\(^{-1}\) and 10–20 mm h\(^{-1}\)), we selected only 20 events of this intensity class to reduce the computation load. For the other rainfall event classes with higher peak intensities, we considered all extracted events for simulation. As a result, 301 events with different peak intensities were considered, varying from frequent small rainfall events to extreme large storms. The events selected for the detailed analysis are described in Table 4. The intensity time series of three selected events for the first 6 h and 40 min are presented in Fig. 3.

| Event ID | Peak intensity (mm h\(^{-1}\)) | Classification | Duration | Purpose            |
|----------|-------------------------------|----------------|----------|--------------------|
| 5771     | 15.0                          | small          | 1 h 50 min | sensitivity and FCD location |
| 5423     | 27.6                          | small          | 14 h 10 min | sensitivity, FCD location and control details |
| 4210     | 20.4                          | small          | 19 h      | sensitivity, FCD location |
| 5643     | 48.0                          | Medium-sized   | 27 h 20 min | FCD location and control details |
| 4829     | 88.2                          | large          | 28 h 50 min | FCD location and control details |

4. Results and discussion

In this section, we first discuss the sensitivity analysis of the proposed control rules (different FCD opening parameters) on the reduction of CSOs. With a better understanding of the parameter setting, we use a single set of FCD opening rule parameters and discuss control strategy efficiency based on a large number of rainfall events with different peak intensities and different spatial locations of the FCD. The flow dynamic process and control mechanism is also investigated and discussed.

4.1. Sensitivity analysis on control parameters and impact of FCD location on CSO reduction

To evaluate the influence of the FCD control parameters, we selected three small rainfall events: 5771, 5423 and 4210 (ranging from short to long duration). We also investigated the effect of the FCD location on parameter sensitivity (only for rainfall event 5771); since FCD-4 and FCD-5 did not show successful flow control cases, the sensitivity analysis was conducted only with FCD-1, FCD-2 and FCD-3. According to the SI values presented in Table 5, CSO reduction volume was not sensitive to all parameters in FCD control strategy for the selected cases and FCD locations. It is observed that the SI values for \(a_1\) and \(a_2\) are substantially smaller than the values for \(a_3\) and \(a_4\); this indicates that \(a_3\) and \(a_4\) affect the control performance. Specifically, \(a_3\) and \(a_4\) reflect the control reaction under low water level conditions, namely large rainfall intensity-low water level (Le-Lw) and small rainfall intensity-low water level (Si-Lw). Based on the results, we see that low water level is the most frequent condition that we deal with during the flow control process. This is understandable as the small rainfall events generate low flow rate.

In order to see how medium-sized to large rainfall event respond to flow control, we also chose event 5643 (peak rainfall intensity of around 50 mm h\(^{-1}\)) and event 4829 (peak rainfall intensity of around 90 mm h\(^{-1}\)) to conduct the analysis using a large number of rainfall events with different peak intensities, as shown in Table 3. Since most of the rainfall events fall in the range of small peak intensities (0–10 mm h\(^{-1}\) and 10–20 mm h\(^{-1}\)), we selected only 20 events of this intensity class to reduce the computation load. For the other rainfall event classes with higher peak intensities, we considered all extracted events for simulation. As a result, 301 events with different peak intensities were considered, varying from frequent small rainfall events to extreme large storms.

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After using the largest opening value in the parameter space, i.e., \((\alpha_1, \alpha_2, \alpha_3, \alpha_4) = (0.5, 0.5, 0.5, 0.5)\), the flood volume was larger than without flow control (Table 6), which makes control operation infeasible under these rainfall conditions. Based on these results, no further analysis on parameter sensitivity was conducted as, for these two rainfall events, a lower FCD opening value would most likely increase flooding in the system.

In a following step, we further investigated the maximum CSO reduction by varying the two most dominant control rules parameters, i.e., parameters \(\alpha_3\) and \(\alpha_4\). We used the five scenarios with different events and different FCD locations presented in Table 5 (event 5771 with FCD-1, FCD-2, FCD3, event 5423 with FCD-1 and event 4210 with FCD-1) to evaluate the best parameter setting. The total CSO reduction volume for each \(\alpha_3\) and \(\alpha_4\) combination is calculated by aggregating the results of the five scenarios. In Fig. 4 it can be seen that the largest total CSO reduction volume that could be obtained was using \(\alpha_3\) and \(\alpha_4\) equal to 0.3 and 0.1, respectively, indicating that for the selected events and FCD locations, the average better performance is achieved when \((\alpha_3, \alpha_4)\) assume these values. Based on the low sensitivity for \(\alpha_1\) and \(\alpha_2\), we subjectively assign a larger value (0.5) to \(\alpha_1\) (large rainfall-high water level) and a lower value (0.2) to \(\alpha_2\) (small rainfall-high water level). Since it was not possible to check the parameter sensitivity using all rainfall events due to computational and time resources limitations, for the subsequent analyses presented in this study the following FCD control parameter setting obtained based on the aforementioned analysis was used: \((\alpha_1, \alpha_2, \alpha_3, \alpha_4)\) as (0.5, 0.2, 0.3, 0.1).

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### Table 5

| Control rule parameter | Rainfall event IDs | 5771 | 5423 | 4210 |
|------------------------|-------------------|------|------|------|
| \(\alpha_1\)           | 1.01              | 0.00 | 0.00 | 0.00 |
| \(\alpha_2\)           | 0.28              | 0.00 | 8.96 | 0.00 |
| \(\alpha_3\)           | 67.35             | 101.26 | 17.96 | 27.34 |
| \(\alpha_4\)           | 211.19            | 246.47 | 90.84 | 263.32 |

Large SI values are marked as bold.

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### Table 6

| Rainfall events (ID) | Scenario       | CSO (m³) | Flood (m³) | WWTP (m³) |
|----------------------|----------------|----------|------------|-----------|
| 5643                 | no control     | 2889.6   | 5.5        | 23,165.0  |
|                      | with FCD-1     | 2886.4   | 15.0       | 23,155.4  |
| 4829                 | no control     | 7027.2   | 338.5      | 12,405.8  |
|                      | with FCD-1     | 6702.8   | 624.6      | 12,459.1  |

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**Fig. 3.** Rainfall intensity time series of events ID 5423 (small), 5643 (medium-sized) and 4829 (large).

**Fig. 4.** Total CSO reduction volume with different \(\alpha_3\) and \(\alpha_4\) for the following five scenarios with small intensity rainfall events: event 5771 with FCD-1; event 5771 with FCD-2; event 5771 with FCD-3; event 5423 with FCD-1; event 4210 with FCD-1.
4.2. Analysis of CSO reduction with different FCD locations

From the analysis above, we already have a preliminary understanding that the control efficiency depends on rainfall intensity; for a large rainstorm (i.e., high peak intensity), the FCD control strategy could not reduce CSO without causing flooding. To investigate how the proposed FCD control strategy performs in the long term, we used 301 simulations corresponding to the rainfall events presented in Table 3 (Section 3.2). In addition, the effect of the different FCD locations was also studied, considering six different locations. The performance of the proposed FCD control strategy and of the different FCD locations are reported in Tables 7 and 8.

As can be seen from the figures in Table 7, FCD-1 location shows the largest number of successful simulations, i.e., simulations with reduced CSO discharges and with no increased flooding. The relative percentage of successful simulations are also presented under different rainfall peak intensities. For rainfall events with peak intensity over 60 mm h⁻¹, the control strategy was not able to produce successful results, therefore, for the sake of simplicity, this class of rainfall peak intensity was not included in Table 7.

It was found that FCD-1, FCD-2 and FCD-3 could achieve the largest CSO reduction potential, especially for rainfall events with peak intensity between 10–20 mm h⁻¹. The obtained results indicate that with the proposed control strategy and settings, one can achieve some CSO reduction in around 80 out of 100 CSO events; this was found for FCD locations FCD-1, FCD-2 or FCD-3. When considering larger intensity rainfall events, one could see, as expected, that the rate of success is significantly reduced. Nevertheless, this reduction should not be underestimated as smaller events are more frequent than larger ones, and, in the long term, the impact of the more frequent CSO cannot be disregarded.

Regarding the total CSO reduction volume, the control strategy is also more efficient for rainfall events with peak intensity between 10 and 20 mm h⁻¹, and between 20 and 30 mm h⁻¹. As can be seen in Table 8, though relative percentage of CSO volume reduction is lower than 6%, the absolute CSO reduction volume is not negligible in the long term, e.g., up to 2722.9 m³ with FCD-1 for the 301 simulated events.

Based on the results presented in Tables 7 and 8, one can say that the FCDs located more downstream (FCD-4 and FCD-5) almost seldom work under the proposed control strategy. This may be associated with the limited space in the system that could be more difficult at downstream parts of the system that receive larger flow contributions from the catchment. The CSO reduction using FCD-β should be zero as it is located downstream of the CSO structures. However, the results showed a relatively low CSO reduction (5.5 m³) at this location, which is indicative of numerical model instabilities. This provides an estimate of the results error associated with numerical errors caused by the inclusion of dynamic FCD operation.

From the available-storage point of view, one may expect better performance in CSO reduction for the smallest rainfall intensity bracket, 0–10 mm h⁻¹, compared to 10–20 mm h⁻¹. However, the control algorithm proposed in this study was designed to be more effective for larger CSO volumes, with its primary dependence on water level in the pipes and relative rainfall intensities. For the smallest rainfall events the CSO magnitudes are also relatively small (an order of magnitude smaller in 0–10 mm h⁻¹ compared to 10–20 mm h⁻¹) and occur over much shorter durations. The control rules are therefore not able to reduce overflow volume for very small, short-duration CSO events that require faster control dynamics.

To better understand why FCD-4 and FCD-5 could not contribute to reduce CSOs, the fill-up percentage of the pipes right upstream of the FCD locations during peak water level for the experiment using five events is presented in Table 9. Based on the maximum fill-up percentage, FCD-2 has the lowest filling percentage among the five locations. Also, FCD-1, FCD2 and FCD-3 have lower fill-up percentage than FCD-4 and FCD-5. For example, with event 5423 pipe filling percentage is lower than 50% for FCD-1, FCD-2 and FCD-3, while at the FCD-4 and FCD-5 locations, all pipes almost reach their maximum capacity (filling percentage between 78.6 and 100%). For the specific case of this particular network and even for a low intensity rainfall event, we could see that for the two most downstream locations, the pipes located right upstream of the FCDs become close to full. This indicates that there is very little room for in-sewer storage in these locations and consequently the low performance of FCD-4 and FCD-5.

According to the statistical analysis of the 301 rainfall simulations and pipe filling conditions (see Fig. 5), it is shown that the “accumulation effect” in the sewer network is critical to the control efficiency. That is to say, flow control becomes more challenging when water accumulates and fills up the downstream pipes. Fig. 5 presents the distribution of CSO reduction volume and flood increase volume for the six FCD locations.

### Table 7

| FCDs | Number of successful cases | Rainfall peak intensity (mm·h⁻¹, interval of 10 min) |
|------|-----------------------------|---------------------------------------------------|
|      |                             | 0–10 | 10–20 | 20–30 | 30–40 | 40–50 | 50–60 |
| FCD-1| 107                         | 25%  | 85%   | 57.4% | 10%   | 0%    | 5.9%  |
| FCD-2| 79                          | 30%  | 80%   | 33.8% | 10%   | 4.2%  | 0%    |
| FCD-3| 69                          | 40%  | 75%   | 33.1% | 1.7%  | 0%    | 0%    |
| FCD-4| 4                           | 20%  | 0%    | 0%    | 0%    | 0%    | 0%    |
| FCD-5| 16                          | 55%  | 15%   | 1.5%  | 0%    | 0%    | 0%    |
| FCD-β| 11                          | 10%  | 0%    | 5.2%  | 1.7%  | 4.2%  | 0%    |

The largest percentages are marked as bold.

### Table 8

| FCDs | Total reduction volume (m³) | Rainfall peak intensity (mm·h⁻¹, interval of 10 min) |
|------|----------------------------|---------------------------------------------------|
|      |                            | 0–10 | 10–20 | 20–30 | 30–40 | 40–50 | 50–60 |
| FCD-1| 2722.9                     | 0.6% | 2.5%  | 2.7%  | 0.4%  | 0%    | 0%    |
| FCD-2| 2636.4                     | 0.6% | 6.0%  | 2.0%  | 1.1%  | 0.1%  | 0%    |
| FCD-3| 1000.7                     | 2.8% | 4.4%  | 0.9%  | 0.1%  | 0%    | 0%    |
| FCD-4| 0                          | 0%   | 0%    | 0%    | 0%    | 0%    | 0%    |
| FCD-5| 26.3                       | 3.5% | 0.3%  | 0%    | 0%    | 0%    | 0%    |
| FCD-β| 5.5                        | 0%   | 0%    | 0%    | 0%    | 0%    | 0%    |

The largest percentage is marked as bold.

### Table 9

| FCDs | Upstream pipe ID | Fill-up percentage |
|------|------------------|--------------------|
|      | Event | Event | Event | Event | Event |
|      | 5771  | 5423  | 4210  | 5643  | 4829  |
| FCD-1| L448-L459 | 31.4% | 35.7% | 28.6% | 50%   | 80%   |
| FCD-2| L120-L126 | 24%  | 31%   | 23%   | 44%   | 71%   |
| FCD-3| 126-128a  | 41.6% | 49.6% | 38.4% | 60.8% | 95.2% |
| FCD-4| 162-163  | 100%  | 100%  | 100%  | 100%  | 100%  |
| FCD-5| 47-47a   | 54.3% | 78.6% | 57.1% | 100%  | 100%  |
| FCD-β| 593-594  | 87.1% | 94.3% | 74.3% | 100%  | 100%  |

The lowest fill-up percentages are marked as bold.
locations. FCD-2 shows more CSO reduction and less flood increase in terms of maximum value, which is consistent to the results in Table 9. FCD-2 represents the best choice to reduce CSO in the system while maintaining minimal flooding.

To further explain the location effect, upstream pipe size and filling up percentage during the peak water level for event 5771 is shown in Fig. 6. It is observed that FCD-3 has the largest upstream pipe diameter but the lowest filling up percentage is at FCD-2. Compared with the CSO reduction performance in Fig. 5, FCD-2 has a higher CSO reduction volume, showing that in-sewer storage is not always directly related to the pipe diameter. The “effective storage volume” rather than the physical storage volume depends on the system hydraulics dynamics and how much the pipe is filled with water during the simulation – this aspect is critical to the success of flow control in a space-constrained sewer network. This finding helps improve our understanding of the real in-sewer capacity with regard to the rainfall process and hydraulic simulations.

4.3. Flow dynamics and control mechanism

The control strategy proposed to reduce CSO discharges changes the flow dynamics in the pipe network. Ideally, net CSO discharge through the overflow structure should be reduced with FCD installation and a larger volume of wastewater and stormwater should reach WWTP for treatment. General information is checked with total inflow volume at the two different CSO structures, the inflow to the WWTP, and a metric regarded as the net flood volume. The comparison between no control and with FCD control is presented in Table 10. It is noted that only under event 5423 (small peak event) could a CSO reduction of 37.2 m³ be achieved without increasing flood. For the medium-sized and large rainfall events, CSO reduction is at the expense of additional flood in the network. Another finding specific to the network used in this study was that the CSO reduction was mainly obtained at CSO-1 location, which is located more upstream in the system. This finding indicates that the flow control works by blocking the upstream low flow from reaching the main pipe and thereby reducing the contribution to total overflow volume.

Fig. 7 shows the water level at the control node, FCD operation curve and inflow rate at CSO-1, CSO-2 and WWTP locations throughout the simulation for the three rainfall events. For the small event 5423, the FCD operation is more stable than other two events. Seen from the opening curve, FCD-1 was closed to 0.1 since the simulation started. The partial closure of FCD-1 reduces CSO for the upstream system, indicated by the inflow rate decrease after 13 h at CSO-1. Then FCD was open from

![Fig. 5. CSO reduction and flood increase volume with different FCD.](image1)

![Fig. 6. Upstream pipe diameter and filling up percentage of different FCD for event 5771.](image2)
0.1 to 0.3, which reacted to an incoming small rainfall peak and subsequent higher water level in the pipe to avoid flooding. For the medium-sized event 5643 and large event 4829, the closing of FCD reduced CSO during several flow peaks at CSO-1 but immediately increased water level in the upstream control node. Water level was increasing with the incoming rainfall peak and jumped even higher once the FCD was further closed. To avoid flooding, the FCD was opened frequently to a larger percentage to decrease the water level in the system. Under a high rainfall intensity, the flow control to store water in the pipe is both risky and unstable. First, the water level in the pipe is already high with the intensive rainfall peak and will easily reach the maximum level with FCD blocking (e.g., water level curve for event 4829 with maximum node depth of 3.2 m). Second, the instability of FCD operation is conceivable with dynamic control, since the FCD needs to be operated fast enough to mitigate flood risk. From Fig. 7, almost no changes in the inflow curve at both CSO-2 and WWTP location can be observed. To see the slight variations of the inflow at these locations, a zoom-in is presented in Fig. 8 for event 5423. The slight CSO increase at CSO-2 (Fig. 8a) and WWTP (Fig. 8b) happens because the water is only stored in the pipe temporarily - the closing of FCD holds water behind the FCD and releases it once FCD opens again.

The flow control caused also some side effects, i.e., the accumulated backwater causing more flood volume upstream of the FCD, e.g., the control manhole. With the FCD open to a larger value in advance of the flow peak, the excessive water still caused unavoidable flood, which is also confirmed from the sensitivity analysis (with FCD opening setting to 50%). Based on the results, we could see that from a medium-sized to large rainfall events, the space-constrained system was unable to deal with intensive and rapidly-incoming rainfall. Moving one step further, flow control did not work and could even worsen flooding under such storm events. From this event-based analysis, we see that the dynamics of flow control process shows more complexity than a static utilization of unused in-sewer storage. Control strategy in a space-limited system works by making use of the pipe storage during a low flow but needs to take into account the water accumulation effect. When more water is expected to enter into the network and the upstream capacity is exploited, FCD needs to be kept fully opened to avoid flooding.

5. Conclusions

In this work, we studied the efficacy of flow control in reducing CSOs when no additional storage space is added to a drainage network, thus operating under space constraints. The motivation is to add to the body of literature on the benefits and pitfalls of flow-control under such inhibiting circumstances. To do this, we implemented a simple flow control strategy within a representative space-limited drainage system...
and examined its feasibility using a long historical rainfall record. Performance analysis on over 300 rainfall events indicated that the flow control employing the already available in-sewer storage can achieve some reduction in CSO volumes, especially for rainfall events with peak intensities between 10 and 20 mm h\(^{-1}\). Nevertheless, this relatively small reduction may have an impact in the long term as they tend to occur frequently and can cumulatively represent a significant volume of discharged wastewater. However, it was shown that almost no improvement can be made to the CSO reduction by just using the in-sewer capacity during large-size rainfall events due to intractable CSO volumes. Besides, for the smallest rainfall intensity bracket, with very small CSOs happening over very short durations, the overflow reduction is also limited. For large CSO events, flooding events start to occur or get further exacerbated when a control mechanism interferes with the flow of a pipe that is already operating close to its design hydraulic capacity. From an operational perspective, municipalities will only consider flow control operation when there is no risk of flooding, as hassle-free conveyance of storm water is one of the primary purposes of combined sewers. However, despite the operational limitations for higher rainfall intensities, more tractable CSO events, e.g., corresponding to 10 and 20 mm h\(^{-1}\) peak rainfall intensities in our study, happen more frequently and the total CSO reduction volume, over long time horizons, is substantial.

When combined with other mitigating strategies, this CSO reduction from small rainfall events will play a role in improving the condition of the receiving water bodies. From our simulations we also learn that, during flow control for space-constrained networks, we need to be particularly cautious about any disruptive water accumulation in the system and tune the control strategy to avoid such side effects. Our findings also reinforce the importance of choosing appropriate flow control locations, highlighting their critical role in deciding the performance of the control strategy. In the presented case study, FCDs located more upstream of the system showed better CSO reduction. This happened as the flow control prevents the upstream low flow from reaching the main pipe, and thus reducing that fraction of contribution to the overflow volume. Besides, the upstream pipes do not get surcharged by large flows that are present at more downstream locations. The successful choice of the control location also depends on the pipe capacity upstream of the FCD and filling up percentage during the rainfall event. In general, results show that the filling up percentage is more critical in the appropriate selection of the flow control site than the total volume of the pipe. This filling up percentage is an indication of the effective pipe storage potential, in contrast to its physical storage space under static conditions.

As a next step towards increasing the robustness of the presented results, future research can explore the performance of different, more sophisticated control strategies with multiple FCDs installations for such space-limited networks.

Credit author statement

Wenqi Wang: Methodology, Software, Visualization, Writing (original draft preparation, reviewing and editing). João P. Leitão: Conceptualization, Methodology, Project administration, Supervision, Writing (reviewing and editing). Omar Wani: Conceptualization, Methodology, Project administration, Supervision, Writing (reviewing and editing).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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