CSO reduction by integrated model predictive control of stormwater inflows: a simulated proof of concept using linear surrogate models

Lund, Nadia Schou Vorndran; Borup, Morten; Madsen, H.; Mark, O.; Mikkelsen, Peter Steen

Published in:
Water Resources Research

Link to article, DOI:
[10.1029/2019wr026272](https://doi.org/10.1029/2019wr026272)

Publication date:
2020

Document Version
Peer reviewed version

[Link back to DTU Orbit](#)

Citation (APA):
Lund, N. S. V., Borup, M., Madsen, H., Mark, O., & Mikkelsen, P. S. (2020). CSO reduction by integrated model predictive control of stormwater inflows: a simulated proof of concept using linear surrogate models. *Water Resources Research*, 56(8), [e2019WR026272]. <https://doi.org/10.1029/2019wr026272>

General rights

Copyright and moral rights for the publications made accessible in the public portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

- Users may download and print one copy of any publication from the public portal for the purpose of private study or research.
- You may not further distribute the material or use it for any profit-making activity or commercial gain
- You may freely distribute the URL identifying the publication in the public portal

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Lund Nadia Schou Vorndran (Orcid ID: 0000-0002-9369-4552)
Madsen Henrik (Orcid ID: 0000-0001-8934-0834)
Mikkelsen Peter Steen (Orcid ID: 0000-0003-3799-0493)

CSO reduction by integrated model predictive control of stormwater inflows: a simulated proof-of-concept using linear surrogate models

N.S.V. Lund^{1A}, M. Borup¹, H. Madsen², O. Mark², and P.S Mikkelsen¹

¹Department of Environmental Engineering (DTU Environment), Technical University of Denmark, Bygningstorvet, Building 115, 2800 Kgs. Lyngby, Denmark

²DHI, Agern Allé 5, 2970 Hørsholm, Denmark

Corresponding author: Nadia Lund (nal@env.dtu.dk)

Key Points:

- Integrated model predictive control of stormwater inflows can reduce overflows; almost as much as disconnecting stormwater from the sewers
- Linearized surrogate models and convex optimization make implementation compatible with the time constraints in an operational setting
- The performance depends on the prediction horizon and the recursive initialization of the surrogate models with a detailed model

^A Current affiliation: EnviDan, Fuglebækvej 1, 2770 Kastrup, Denmark

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1029/2019WR026272

Abstract

Combined sewer overflows (CSO) of mixed stormwater and wastewater pollute nearby receiving surface waters and pose a risk to the environment and human health. We use ‘integrated stormwater inflow control’ to mitigate CSO by dynamically controlling the inflow of stormwater to the combined sewer system in real-time, expanding the physical space of traditional real-time control. This control is carried out with model predictive control (MPC), which we base on convex optimization including a linear internal surrogate model of the controllable above- and belowground infrastructure. A detailed hydrodynamic model is used to evaluate the results and recursively initialize the surrogate model. MPC dynamically decides when to let stormwater enter the sewer system and when to store and convey excess stormwater in the above-ground infrastructure otherwise intended for passive cloudburst management. The performance was quantified in a simulation study in Copenhagen, Denmark, using a 1D distributed hydrodynamic model and 32 rain events from 2016, of which 18 caused CSO in the situation without control. Four of the 18 CSO events were avoided with MPC, and the total CSO volume was reduced by 98.4% of the potential reducible volume. For one event, stormwater was unnecessarily kept on the surface because the surrogate model wrongly predicted a CSO. The computational cost was in all cases compatible with an operational implementation. With the invention of proper actuators for control of stormwater inflows, we show that MPC of stormwater inflows may be a viable supplement to more traditional passive ways of managing stormwater in urban areas.

1 Introduction

Most old cities in Europe and North America are served by combined sewer systems, in which stormwater and wastewater is conveyed in the same pipe system. Exceedance of the capacity of combined sewer systems results in combined sewer overflows (CSOs) causing flow of untreated wastewater into receiving water bodies, which may affect the environment as well as human health.

CSOs are traditionally mitigated by expanding pipes and building detention basins. This can however be infeasible due to high costs and lack of underground space. Alternatively, real-time control methods can be applied to optimize the usage of the existing system capacity (García et al., 2015; Lund et al., 2018; Schütze et al., 2004), but the potential of these optimization methods is constrained by limitations of the underground storage and conveyance capacities. Another solution is to reduce the inflow to the system by managing stormwater in local stormwater control measures (SCMs) placed above ground, also referred to as LIDs (low impact developments), SUDS (sustainable urban drainage systems) or WSUD (water sensitive urban design), see Fletcher et al. (2015). One such solution is “street storage” as implemented in two US cities in the 1990s (Carr et al., 2001; Nakai & Carr, 1993; Walesh, 2000; Walesh & Esposito, 2004). The concept includes disconnecting roof downspouts and the installation of passive flow regulators with a fixed capacity in the gully pots where surface runoff is entering the sewer system. The remaining water is stored in reshaped streets with enhanced storage capacity. In general, local SCMs are rarely controlled in real time, and the innovation of suitable technology to activate these dynamically are rarely described in literature as, for example, the recently developed ‘cloudburst valve’ (Leth & Christensen, 2016), which disconnects downspouts only for major rain events to avoid overloading the combined sewer.

Cloudbursts are short-duration, intense rainfall events that can cause disruption of critical functions in the city due to flash flooding (Rosenzweig et al., 2019). Such extreme rain events have in many places become both heavier and more frequent, which has caused severe flooding of urban areas in recent years. This is predicted to increase further in the years to come (Fowler & Hennessy, 1995; Sunyer et al., 2015) and has led to the development of the Nature Based Solutions (Kabisch et al., 2016) and Sponge City (Li et al., 2017) concepts in Europe and China, respectively, which has similarities with earlier work on “designing with nature” (McHarg, 1969) and comprise many types of SCMs. The city of Copenhagen, Denmark, experienced five major cloudbursts causing pluvial flooding in the period 2010-2015, which led to the formulation of the Copenhagen Climate change adaptation and investment statement (City of Copenhagen, 2015). This outlines the construction of 300 cloudburst management projects to be implemented over a time span of 20 years. These projects include grey (such as street storage and conveyance) and green (such as vegetated detention ponds) infrastructure (hereunder SCMs) aimed to provide conveyance and storage of excessive stormwater flows and volumes above ground, in addition to creating additional amenity value (Madsen et al., 2017). There is an intent to use these cloudburst management solutions more often than just during the rare extreme events, for example, for controlling minor and medium-sized rain events that otherwise cause CSO to occur, but no plans have yet been put forward.

We currently see two parallel, but until now disconnected technological paths promoted, namely on one side aboveground management of stormwater (including SCMs, Nature Based Solutions, Sponge Cities and above-ground cloudburst management), and on the other side the Smart Cities concept (including sensing and intelligent control of sewer systems (Eggimann et al., 2017; Kerkez et al., 2016)). Combining these two trends in a dynamic and greener version of the passive street storage gives rise to new methodological and technological developments. The underlying idea in the current article is to dynamically control the inflow of stormwater to the combined sewer system in real-time during minor to medium sized rain events. By keeping stormwater above ground and enhancing the use of above-ground green and grey infrastructure, hereunder cloudburst infrastructure in the urban landscape, we can mitigate problems related to CSO occurrences caused by limited capacity of the underground system and of traditional small-sized SCMs. This concept thus expands the physical space of traditional real-time control to cover underground as well as surface infrastructure. Keeping stormwater runoff intentionally on the surface may at first sound risky. However, the cloudburst infrastructure is designed to safely convey and store stormwater during much larger extreme rain events and will thus also be safe to use during minor and medium-sized rain events. Other general nuisances from keeping stormwater on the surface may potentially be integrated into the control optimization (Lund et al., 2019a).

The general perspective of this real-time dynamic control is introduced as ‘integrated stormwater inflow control’ in Lund et al. (2019a). The present paper applies the concept on a simulated proof-of-concept study for a real catchment in Copenhagen containing a local cloudburst project with existing above-ground storage and conveyance properties. Model predictive control (MPC) is, based on rainfall forecasts, used to control when to let stormwater enter the underground sewer system through the stormwater inlets and when to shut the inlets and use the above-ground infrastructure. Hereby, the above-ground infrastructure is used also during minor and medium-sized rain events that would otherwise cause CSO, and the concept furthermore has notable resilience, liveability and sustainability benefits. The concept is implemented using a newly developed MPC framework for water systems (Madsen et al., 2018) that is based on linearized models and computationally efficient (convex) optimization methods. While Lund et al. (2019a) only presents the overall

concept and selected results, the present paper thoroughly explains the underlying MPC method used to generate the results and furthermore expands and performs in-depth analyses of results from 18 overflow events and 14 non-CSO-producing events during a whole year, which is more than what most MPC studies use for evaluation (Lund et al., 2018). The present paper furthermore includes a thorough description of how a 1D distributed high-fidelity (HiFi) model can be used for performance evaluation as well as initialization of the internal MPC model, which is rarely done in urban drainage MPC literature (Lund et al., 2018). Also, this paper investigates the effect of different prediction horizons used in the MPC for control optimization, which is commonly not investigated in urban drainage MPC literature (Lund et al., 2018), and also of using a ‘safety factor’ on the CSO structure volume to compensate for inaccuracies in the simplified linear internal MPC model.

2 Study area, high-fidelity model and data

2.1 Study area

The Lyngholm cloudburst project is one among 300 planned cloudburst management projects in Copenhagen and includes a cloudburst road (Lyngholmvej, shaped to safely transport water on the surface) and a retention space (Damhusengen, a meadow designed to store water), located in the centre of the study area (Figure 1). The area is served by a combined sewer system that leads mixed wastewater and stormwater runoff from impervious areas to a frequently overflowing CSO structure, from where it flows either southwards through a throttle pipe or, when the volumetric capacity of the overflow structure (49.8 m^3) is reached, over a weir and into the Harrestrup Stream. The subcatchments connected to the pipes below the cloudburst road (the “controllable area”) makes up approximately 7% of the overall 1.48 km^2 study area. The remaining 93% of the area located outside the planned cloudburst project is not dynamically controlled in this simulated proof-of-concept study.

MPC dynamically controls when stormwater runoff from the controllable area should enter the combined sewer system (the normal pathway through the inlets and into the sewer system, when no overflow is anticipated) and when it should be prevented from entering the sewer system (when overflows otherwise seem inevitable). Here, the stormwater is instead conveyed on the cloudburst road and subsequently stored in the retention space, from where it is pumped back to the CSO structure when there is available capacity. As the retention space will ultimately be designed for cloudbursts, it will only reach its capacity and overflow into Harrestrup Stream during very large rain events. This is beyond the scope of this study and thus not further addressed here.

2.2 HiFi model

A detailed 1D hydrodynamic urban drainage model of the catchment was obtained from the Greater Copenhagen Utility Company (HOFOR), who routinely re-calibrates and improves the model. The model is constructed in MIKE URBAN (DHI, 2016a), which solves the governing 1D Saint-Venant equations for hydrodynamic simulations of the sewer system. In addition, it supports different rainfall-runoff models for simulating runoff entering the system and simulation of different structures, such as pumps, weirs and valves and corresponding control strategies. This will be referred to as the HiFi (high fidelity) model. The version of the model used in this study contains only the relevant area (Figure 1b) with 97 links and 233 nodes, including one CSO structure that is studied here. This model covers a total area of 2.24 km^2 , including the 1.48 km^2 area routing combined sewage to the CSO structure. Minor alterations were made to the model obtained from HOFOR in order to represent the cloudburst road (as a 1D-1D hydraulic model component), the controllable

inlets from the road to the sewer system (as controllable gates), a retention space of 12,540 m³ placed at the meadow (as a basin), and the pump between the retention space and the CSO structure – see Text S1 in the supplementary information (SI) for more details. The size and shape of the road and retention space were based on physical inspections and assessments of what can realistically be implemented in the area.

2.3 Data

32 rain events from 2016 with magnitudes corresponding to return periods of up to two years (based on intensity over a one-hour duration) are used to evaluate the performance of integrated stormwater inflow control. This includes all 18 events where the HiFi model produced CSO in 2016 and the 14 largest events that did not. The latter are included to examine if MPC unnecessarily results in either CSO or in keeping stormwater on the surface. The rain data has been obtained from a gauge in the Danish Water Pollution Control Committee network ((Jørgensen et al., 1998), gauge 5710) that is situated within two km of the cloudburst road (Figure 1b). We consider a single rain gauge sufficient due to the limited spatial extent of the controllable area.

Figure 1. Case study area (adapted from Lund et al, 2019a). **(a)** Cloudburst solutions and sewer system close to the controllable area. **(b)** Overview of the HiFi model with an indication of the total area that discharges water to the CSO structure as well as the controllable area. Contains digital maps from the Danish Agency for Data Supply and Efficiency, Map 6170_710, November 2016.

3 Theory and methods: model predictive control

Model predictive control (MPC) is an adaptive control strategy where the optimal control is recursively recalculated over a specified, finite time horizon based on information about the current state of the sewer system (from a HiFi model and/or from measurements) as well as new rainfall forecasts. This paper follows the MPC terminology and categorization defined in Lund et al. (2018). Below we describe the MPC framework used, the specific

implementation designed for the purpose at hand, and the methodology used for performance evaluation.

3.1 General MPC framework

In this paper, MPC was performed by applying the recently developed framework in MIKE OPERATIONS (DHI, 2016b; Madsen et al., 2018). Some literature favors using non-linear programming in the MPC solution, which allows for a detailed description of system dynamics (e.g. Zimmer et al., 2015, 2018) but comes with a heavy computational burden. The framework used here instead uses convex programming, which is computationally less demanding but requires that system dynamics are simplified using linear surrogate models. Lund et al. (2018) discuss pros and cons of these two approaches, including the many trade-offs involved in designing an MPC solution. Our intention here is not to compare such different approaches, but to document a novel implementation based on convex optimization for the specific application at hand.

3.1.1 Receding horizon principle

Figure 2 shows, with inspiration from Zimmer et al. (2015, 2018), a flow chart of the MPC process based on the receding horizon principle (the recursive optimization of the control actions over a finite time horizon). First, a rainfall-runoff input model is used to translate rainfall forecasts into flow forecasts over the finite time horizon denoted the ‘prediction horizon’ (1). These boundary inflows are then used to force an ‘internal MPC model’ to find the optimal controllable flows (‘control actions’) in the system over the prediction horizon (2). Here, the ‘setting duration’ describes how often these control actions change over the course of the prediction horizon. Once the optimized control actions have been determined, the optimized control actions from the first part of the horizon (the ‘sampling interval’) are transferred as time-varying flow set-points to actuators in the sewer system (typically via a SCADA system), which are translated to actual actuator settings using PID controllers (3). This first part of the control actions is furthermore used to advance a HiFi model (which may also have been assimilated with available sensor measurements) (3), and the prediction horizon is moved forward in time (4). The HiFi model results give a more realistic picture of the effect of the optimized control than the results from the internal MPC model and are therefore, possibly in combination with sensor measurements, used to initialize the states in the internal MPC model after each sampling interval (5) before the entire process is repeated using updated input forecast information.

Figure 2. Flow chart of the applied recursive MPC process.

Figure 3 shows the MPC process with emphasis on the effect of initializing the internal MPC model state (here, pipe discharges and basin volumes) from the HiFi model. Two overall scenarios are shown: one where initialization is used (the upper, purple and black set of curves) and one where initialization is omitted (the lower, yellow set of curves). For each initialization (shown for times 5, 10 and 15 minutes) the internal MPC model takes the state values of the HiFi model as starting point before each new optimization. The parameters of the internal MPC model however stay the same. In Figure 3, the sampling time is exemplified as 5 minutes and the prediction horizon is 120 minutes. The setting duration is not shown. At the time of forecast (shown at time 15 minutes), the optimal control actions are found, resulting in an optimized internal MPC model forecast. The first part of the control actions is realized in the HiFi model, and the results are used to initialize the internal MPC model, which once again makes a prediction into the future. Without initialization (lower, yellow curves), the internal MPC model will drift away from the HiFi model and, since the HiFi model likely represents reality better, also from the ‘simulated truth’.

Figure 3. MPC process with focus on the effect of initializing the internal MPC model with HiFi model results, compared with no initialization.

3.1.2 Optimization

The optimization (step 2 in Figure 2) finds the best control actions based on the boundary inflows from the input model, the internal MPC model (describing the system dynamics), an optimization model (describing the optimization problem) and an optimization solver (carrying out the optimization). The optimisation model is formulated as a convex optimization problem, which allows optimisation of control of large sewer systems with numerous actuators within seconds or a few minutes (Lund et al., 2018). This, however, sets certain constraints on the internal MPC model, the optimization model and the optimization solver. The following paragraphs elaborate on this and on the overall features of the MPC framework applied.

To ensure convexity of the optimization problem, the MPC framework uses a linearized surrogate model as internal MPC model. The surrogate model is constructed using a modular framework where network elements are connected into one model. The network elements include *reservoirs/basins*, *linear reservoirs* and *pipes*. *Reservoirs/basins* are modelled as simple mass balances and have controlled outflows (i.e. the outflows are determined by the MPC) that are used to represent actuators such as pumps and controllable inlets. The inflows can be either controlled or uncontrolled. *Linear reservoirs* are modelled similarly to *reservoirs/basins* but have an uncontrolled outflow, Q , which depends linearly on the storage volume, S :

$$S = kQ \quad (1)$$

where k is a reservoir time constant that needs to be specified (or calibrated). *Pipes* are simply translating the flow without accounting for diffusion or backwater effects, meaning that the water entering a pipe at time t leaves the pipe at time $t+t_{trans}$, where t_{trans} is the travel time that needs to be specified (calibrated). Water can also enter and leave the pipe along the length of the pipe as “lateral flows”, which can be used to represent controllable inlets or pumps along the pipe.

The optimization model consists of optimization variables, constraints and an objective function, which weighs different objectives against each other. Constraints are formulated as linear constraints, which can be both hard (cannot be violated) and soft (can be violated but with an associated penalty). The objective function includes terms that measure deviations from the preferred system state, violations of soft constraints as well as the value of control actions. The optimisation is then formulated as a quadratic program, which is solved using the MOSEK solver (MOSEK, 2018) that uses an interior-point optimization algorithm.

3.2 MPC implementation for integrated stormwater inflow control

3.2.1 internal MPC model

The boundaries between the input model and the internal MPC model were determined such that the internal MPC model contains only the parts of the sewer system that are affected by the control, while the input model describes the unaffected part of the sewer system and feeds the internal MPC model with input time series (see Figure 2). Due to the dynamic and non-linear behaviour of urban drainage systems it is however not trivial to make a clear division between the internal MPC model and the input model. Figure 4 shows our conceptualization of the case study area (Figure 1) into an internal MPC model and its inputs, consisting of runoff inflows from three lumped sub-catchments to the cloudburst road (pink arrows, accounting for flow from 7% of the total surface area), and six sewage inflows from other parts of the sewer system (yellow arrows, accounting for flow from the remaining 93% of the area). We used the HiFi model of the considered catchment to generate the inputs.

The internal MPC model was constructed using the *reservoir/basin*, *linear reservoir* and *pipe* network elements. It was constructed as a surrogate model (emulator) of the HiFi model, and the parameters of the different elements of the internal MPC model were therefore chosen based on the physical layout of the system described in the HiFi model and from calibration against HiFi model simulations. The following paragraphs briefly explain the internal MPC model while detailed information is found in the supplementary information (SI, Text S2-a about the cloudburst roads and sewer pipes, Text S2-b about the CSO structure, and Text S2-c about the retention space).

The internal MPC model contains the two routes from the cloudburst road to the CSO structure: one through three lumped conceptual inlets (representing multiple sewer inlets) and the sewer system, and one that uses the cloudburst road and retention space. The distribution of stormwater between these two flow paths depends on the control of the three inlets and the pump between the two reservoirs.

Pipe model elements were used to represent the cloudburst road and sewer pipes, and the HiFi model was used as reference to estimate their flow capacities and flow times. This resulted in a total flow time on the cloudburst road of 21.8 min and a total flow time in the sewer network of 18.3 min.

Figure 4. Internal MPC model structure and inputs. Colors resemble those used in Figure 1.

The CSO structure and its uncontrolled throttle pipe outflow was modelled as a *linear reservoir*. Backwater effects occur in some of the adjacent pipes (both in internal MPC model pipe elements and in inputs) when the CSO structure fills up; thus, these pipes serve as additional storage capacity in the system. This storage capacity was estimated from HiFi model simulations and included in the CSO structure volume in the internal MPC model by increasing it from 49.8 m³ to 909.3 m³. Furthermore, discrepancies between the internal MPC model and the HiFi model can generate CSO in the HiFi model that is not intended by the MPC. These can arise because the PID controllers in the HiFi model do not always deliver exactly the flow specified by the MPC and thus accidentally may discharge more water through the inlets. The simplified internal MPC model, for example, also assumes that the flow time in the system is constant. Discrepancies also arise due to backwater-affected inputs, which cannot be taken explicitly into account by the MPC since the internal model cannot affect the input flows. To counteract the negative effects of these discrepancies, a safety factor of 5% was included by reducing the total CSO structure volume to 863.8 m³. Hereby, the internal MPC model predicts an overflow when the CSO structure is only 95% full, which implies that the control scheme will tend to start to keep water on terrain a bit earlier than required but with the positive effect that small overflows due to model deficiencies are avoided. The linear reservoir constant k was determined from the relationship between the volume of the CSO structure and the throttle flow in the HiFi model, which corresponds to a mean residence time in the basin of 55.3 min. It is not possible to explicitly model non-linear phenomena in the linearized internal MPC model, and the CSO was therefore included as a controlled outflow, even though this is not the case in reality (i.e. it is fictitiously controlled). The reduction of overflow was achieved by penalizing this flow in the objective function, as also done by Fiorelli et al. (2013), Fiorelli and Schutz (2009) and Gelormino and Ricker (1994).

We used a *reservoir* with a controlled outlet with a maximum capacity of 0.4 m³/s to represent the retention space and the maximum pump rate between this and the CSO structure. The parameters of the reservoir and pump were similar to those in the HiFi model. We modeled overflow from the retention space as a fictitiously controlled outflow and penalized it in the objective function.

3.2.2 Optimization model

The optimization model decides for each iteration how much water enters the sewer system and potentially contributes to overflow, how much flows on the surface to the retention space, and how fast this water returns to the sewer system. The internal MPC model contains six optimization variables: flow through the three inlets to the sewer system, the pump flow rate between the retention space and the CSO structure, and the overflows from the retention space and CSO structure. This results in 12 hard constraints (one upper and one lower per variable). Furthermore, all eight model elements have a lower and upper constraint on either flow or volume – i.e. 16 constraints in total – of which six are soft flow constraints (see details in the supplementary information (SI, Text S3)). Thus, there are 22 hard constraints and 12 decision variables (six optimization variables and six soft constraints) described with a 1-min resolution over the control horizon.

We used a quadratic objective function and eight linear constraint equations to optimize a trajectory of control actions for each controlled flow:

$$J(\hat{\mathbf{u}}) = \sum_{i=1}^{Pred.Hor.} \left(\sum_{m=1}^3 (P_{upper,pipe,m} s_{upper,pipe,i,m}^2) + \sum_{n=1}^3 (P_{lower,road,n} s_{lower,road,i,n}^2 + P_{road} (\hat{y}_{road,i,n} - r_{road})^2) \right) + \sum_{i=0}^{Pred.Hor.-1} \left(P_{pump} (\hat{u}_{pump,i} - r_{pump})^2 + \sum_{k=1}^2 P_{overflow,k} (\hat{u}_{overflow,i,k} - r_{overflow})^2 \right) \quad (2)$$

$$0 \leq \hat{y}_{pipe,i,1} \leq 0.0626 + s_{upper,pipe,i,1}, \quad 0 \leq \hat{y}_{pipe,i,2} \leq 0.202 + s_{upper,pipe,i,2}, \quad 0 \leq \hat{y}_{pipe,i,3} \leq 1.37 + s_{upper,pipe,i,3},$$

$$0 + s_{lower,road,i,n} \leq \hat{y}_{road,i,n} \leq 10, \quad 0 \leq \hat{y}_{throttle\ flow,i,CSO} \leq 0.274, \quad 0 \leq \hat{y}_{volume,i,ret.\ space} \leq 12,540, \quad 0 \leq \hat{u}_{pump,i} \leq 0.4$$

$$, \quad 0 \leq \hat{u}_{overflow,i,k} \leq 10$$

where i is the time index and $Pred.Hor.$ is the prediction horizon. $P_{upper,pipe,m}$ and $P_{lower,road,n}$ are penalties for violation of the (soft) upper pipe constraints and lower cloudburst road constraints, $s_{upper,pipe,i,m}$ and $s_{lower,road,i,n}$, of the m^{th} pipe stretch and n^{th} cloudburst road stretch (marked with the addition of a slack variable 's' in the linear constraint equations). P_{road} , P_{pump} and $P_{overflow,k}$ are penalties of deviating from the target value for the cloudburst road flow, the pump rate, and the overflow rates, r_{road} , r_{pump} and $r_{overflow}$. $\hat{y}_{pipe,i,m}$ is the flow in the m^{th} pipe stretch, $\hat{y}_{road,i,n}$ is the flow on the n^{th} cloudburst road, $\hat{y}_{throttle\ flow,i,CSO}$ is the throttle flow out of the CSO structure, $\hat{y}_{volume,i,ret.\ space}$ is the volume in the retention space, $\hat{u}_{pump,i}$ is the controlled pumping rate from the retention space, and $\hat{u}_{overflow,i,k}$ is the controlled overflow at the k^{th} reservoir (retention space and CSO structure). Choosing meaningful penalties is not a trivial task, especially when the model contains components with different units (see Text S3 in SI for further information (SI, Text S3)). In this case we only have flows in the objective function. Furthermore, using a too large range between the smallest and largest penalties can create issues because changes in terms with a small penalty are less sensitive than changes in terms with a high penalty when the optimizer evaluates the change in the objective function. In this study we attempted to make a logical selection of penalties instead of blind trial-and-error (see SI, Text S3 for details). The resulting penalties are $P_{up,pipe,1} = P_{up,pipe,2} = 10^6$, $P_{up,pipe,3} = 10^4$, $P_{low,road,1} = P_{low,road,2} = P_{low,road,3} = 10^8$, $P_{road} = 10$, $P_{pump} = 10^{-5}$, and $P_{overflow,k} = 10^3$ with target values of $r_{road} = r_{overflow} = 0 \text{ m}^3/\text{s}$ and $r_{pump} = 0.4 \text{ m}^3/\text{s}$.

3.2.3 Receding horizon principle

We tested four different lengths of the prediction horizon: 10 min, 30 min, 60 min and 120 min, the largest reflecting the maximum skilful time horizon expected from radar forecasts (Thorndahl et al., 2017). With a residence time of 55.3 min it takes approximately two hours for a full CSO structure to empty 90%. Increasing the prediction horizon beyond

two hours is therefore not expected to improve the performance of the MPC much further for the size of rain events included in this study. Stormwater has a longer residence time in the retention space than in the CSO structure in the system, calling for a longer prediction horizon for major rain events. However, it is expected that an overflow of stormwater from the retention space will always be preferred over a CSO from the CSO structure, and inclusion of a longer prediction horizon may thus not be necessary even though larger rain events are included. The sampling interval was five minutes and the setting duration was one minute (same as the MPC modelling time step).

The optimization of the control actions over the prediction horizon creates six control trajectories (one for each controlled flow). The first five control actions (i.e. five minutes) from the trajectories from the four physical actuators (the three inlets and the pump) were used as flow set-points for the PID controllers in the HiFi model (their settings can be seen in SI, Text S1). The two fictitiously controlled flows were not transferred to the HiFi model. The HiFi model was run five minutes (equalling the sampling interval) forward in time, and the internal MPC model was re-initialized. The control optimization may become infeasible if the internal MPC model is initialized with values outside the specified constraints for the model elements, for example, if a flow in the HiFi model is negative due to backwater effects. This required an implementation of six soft constraints in the internal MPC model (*Supper,pipe,i,m*, *Slower,road,i,n*, see SI, Text S3).

3.3 MPC performance evaluation

The MPC-optimized control was evaluated by simulating the real-time MPC implementation (see Figure 2) using the HiFi model as ‘simulated truth’ for the 32 rain events. We used historically observed rainfall as forecasted rainfall over the prediction horizon (ex-post forecasting). This implies that the results represent the best-case scenario in terms of rainfall forecast. The MPC scenarios were compared to two base-run scenarios, which were also evaluated using the HiFi model as simulated truth:

- **Baseline scenario (BL):** All stormwater from the controllable area enters the sewer system (open inlets and the pump turned off), corresponding to the present situation.
- **MPC scenarios (MPC-10, MPC-30, MPC-60, MPC-120):** The amount of stormwater entering the sewer system is controlled by MPC using either a 10 min, 30 min, 60 min or 120 min prediction horizon.
- **Maximum CSO reduction (MaxRed):** No stormwater from the controllable area enters the sewer system (closed inlets and the pump turned off), corresponding to the largest achievable CSO reduction.

Thus, MPC was not evaluated on the quality of the internal MPC model predictions as such, but on the quality of the resulting control performance, which is benchmarked against BL (no control) and MaxRed (what could potentially be achieved with a “perfect” control algorithm). We evaluated the results from the three scenarios based on what is penalized in the objective function, i.e.:

- Overflows from the two basins (Section 4.1).
- Flows on the cloudburst road accumulated in the retention space (Section 4.2).
- Removal of water from the retention space (Section 4.3).

Furthermore, we evaluated the effect of the 5% safety factor (Section 4.4) and examined the computational efficiency of the MPC (Section 4.5).

4 Results

4.1 Overflow volumes

As expected, the large retention space did not become completely filled during any of the simulated events. 18 of the 32 rain events gave CSO volumes ranging from 0.3 m^3 to $7,145 \text{ m}^3$ in the BL scenario while only 14 events gave overflow in the MaxRed scenario, and the total overflow volume was reduced from $33,397 \text{ m}^3$ (BL) to $29,173 \text{ m}^3$ (MaxRed) (Figure 5). Using MPC with different prediction horizons performed in-between these two scenarios, as expected.

Figure 5. Number of CSO events and total CSO volume in 2016 for the baseline scenario (BL), the four MPC scenarios with different prediction horizons (MPC-10, MPC-30, MPC-60 and MPC-120) with a 5% safety factor, the MPC-120 scenario without the safety factor (MPC-120 no safe. fact.), and the maximum CSO reduction scenario (MaxRed).

Figure 6 shows the reduction in CSO volume relative to the size of the baseline CSO for the 18 overflow events in 2016 (in %). The reduction with MPC for each CSO event depends on the volume of controllable stormwater relative to the size of the BL overflow. Generally, the larger the overflow volume, the smaller the relative reduction. The horizontal line at 7% represents the stormwater contribution from the controllable area relative to the entire area. For events where the overflow volume is much larger than the controllable stormwater volume, the reduction approaches the relative size of the controllable area, i.e. 7%, as visible in Figure 6. Smaller reductions can however occur in case the MPC or PID controllers do not function optimally (as seen for the 10 min's horizon). A 100% reduction may occur when the CSO volume is smaller than the contribution from the controllable area.

Figures 5 and 6 show that the absolute annual as well as event-based reduction of CSO volumes increase with an increasing prediction horizon, which allows the MPC to be proactive. Increasing the prediction horizon from 30 min to 120 min increased the annual reduction from 9.9% ($3,303 \text{ m}^3$) to 12.4% ($4,135 \text{ m}^3$), which corresponds to 78.6% and 98.4% of the potential reduction of 12.6% achieved by MaxRed, respectively. Using a prediction horizon of 30 min and 60 min only mitigated two of the four avoidable CSO events, while all four were avoided using a horizon of 120 min. The 10 min prediction horizon is shorter than the flow time from the three inlets to the CSO structure (18.3 min). This prevents the MPC from seeing any relation between the inflow of stormwater and CSO. Figures 5 and 6 show a decrease from 18 to 17 CSO events for MPC-10 due to the avoidance of the very small CSO event of 0.3 m^3 ; but this was merely a coincidence.

The MPC optimizations did not cause CSO for any of the 14 rain events that did not give CSO in the baseline situation, which confirms that the MPC optimization works as expected.

Figure 6. Reduction of CSO volume using MPC with prediction horizons from 10-120 min and a 5% safety factor compared to the maximum CSO reduction scenario (MaxRed). The annual reduction is in each case shown in brackets [] in the legend.

4.2 Water on the surface

Figure 7 shows the amount of water stored in the retention space for MPC-120. MPC reduced the CSO volume of all 18 rain events that caused CSO in the BL scenario and water was thus kept on the surface for these events (shown as diamonds). The use of a safety factor will lead to a more frequent use of the surface, but it is not a substantial issue to store too much water on the surface for these 18 events. Water was however stored in the retention space for one of the 14 rain events that did not cause CSO in the BL scenario (shown as a circle); thus, the surface was used unnecessarily. The remaining 13 events did not use the surface and are thus shown on top of each other (triangles).

4.3 Emptying of the retention space

Figure 8 illustrates the filling and emptying of the retention space in the HiFi model for the event on 10/2, 2016, which had the largest CSO volume in the BL scenario ($7,145 \text{ m}^3$) and where MPC therefore also stored most water in the retention space (723 m^3); thus, it had the longest emptying time of the retention space (shorter than 12 hours). The CSO and pump flow hydrographs do not overlap temporally, i.e. the retention space emptied via the pump only after CSO had ceased. Unused storage space was however available in the CSO structure during the emptying of the retention space (indicated by hatched areas in Figure 8b), and the pump rate could thus have been increased to shorten the emptying time. However, the quadratic terms in the objective function favour a constant pumping rate over the prediction horizon which at the end of the horizon will result in an empty retention space; thus the pump rate is not increased by the MPC. Figure 8b also shows that the MPC due to the safety factor will predict a CSO too early as this crest level is reached before the crest level in the HiFi model.

Figure 7. Water stored in the retention space for each event, using MPC-120 with a 5% safety factor. Water was kept unnecessarily on the surface for one event. The events used in Figures 8 and 9 are also indicated.

Figure 8. Emptying of retention space. (a) Outflow and (b) storage behavior in the HiFi model for the largest CSO event, using MPC-120 with a 5% safety factor. The CSO structure never fully empties due to the wastewater in the system, whereas the retention space only contains stormwater runoff and thus empties fully (the last part of the tail is not shown).

4.4 Effect of safety factor

Figure 9 visualizes the MPC and HiFi model results for an event on 9/2, 2016, with (left panels) and without (right panels) safety factor. The sum of the inlet flows is shown (upper panels) as well as the pump rate between the retention space and CSO structure (upper middle panels), the water level in the CSO structure (lower middle panels), and the overflow rate (lower panels). There is an overall good match between the MPC and HiFi model inlet and pump flows, confirming that the PID controllers have been nicely tuned. The inlet flow was larger in the BL scenario in the beginning and end of the event due to the auto-generated water on the surface (see Text S1 in SI). The MPC optimized inlet flow of 0 m³/s resulted in this water being led to the retention space instead. From here it was pumped to the CSO structure, seen as a larger initial pumping rate in the MPC than in BL. When the retention

space was empty (around midnight, to the left in the Figure), the pump stopped. The “jumps” seen most visibly in the MPC CSO flow are due to the initialization of the MPC from the HiFi model.

Figure 9. Results for BL and MPC-120 with (left) and without (right) a 5% safety factor. The upper panels show the total inlet flow, the upper middle panels show the pump rate from the retention space to the CSO structure, the lower middle panels show the water level in the CSO structure (only HiFi model), and the bottom panels show the overflow.

The BL overflow of 62.9 m^3 was reduced to 0 m^3 and 14.5 m^3 with and without the safety factor, respectively. The safety factor purposely makes the MPC predict a CSO much too soon, which resulted in closing of the inlets (Figure 9). When not using a safety factor, the MPC also closed the inlets, but for a shorter period of time. The CSO structure water level was thus closer to the crest level in the HiFi model, and a CSO event therefore actually occurred. Even though the safety factor leads to a larger CSO volume predicted by the internal MPC model, the actual CSO volume will be smaller than not using a safety factor.

Both with and without safety factor, the inlets were opened before the CSO event had ceased in the internal MPC model because the internal MPC model takes the 18.3 min transport time from inlets to CSO structure into account.

With the 5% safety factor, MPC-120 avoided all four possible CSO events and obtained an annual CSO volume reduction of 12.4%. Water was kept unnecessarily on the surface for one event. When not using the safety factor, MPC-120 only avoided one of the four possible CSO events (Figure 5) and the annual reduction in CSO volume decreased to 12.0%. However, no water was unnecessarily kept on the surface. This shows that the safety factor is efficient for trading optimality in terms of number and volume of CSO events and water on the surface.

4.5 Computational cost

The simulations were run on a standard office laptop (Dell Latitude E7450 with processor Intel® Core™ i5-5300U CPU @ 2.30GHz). Running one optimization and subsequently the HiFi model took at most 2 min and 36 sec (experienced for a prediction horizon of 60 min) but was most often less than 1 min. This is less than the five minutes used as sampling interval, which underlines that the presented setup is realistic to implement in an operational setting.

4.6 Discussion

The current simulated proof of concept study only considers a small area and the computational cost shown in Section 4.5 is thus rather limited. However, an operational MPC implementation would likely cover cloudburst infrastructure in a much larger area and thus increase the computational cost, making a fast convex MPC method, such as the one applied in the current study, an attractive approach. The resulting simplified nature of the internal MPC model naturally leads to discrepancies between the internal MPC model and the HiFi model. To account for this and other sources of uncertainty, we used a safety factor of 5% on the CSO structure volume. This resulted in a further decrease in CSO volume and number compared to not using a safety factor but resulted in unnecessary storage of water on the surface. The framework used here thus requires some fine-tuning to function optimally, and it must be up to users to decide on the need for and size of a safety factor. With and without safety factor, MPC reduced the CSO volume by 98.4% and 95.2%, respectively, of the potential reducible volume (MaxRed). This shows that even though the CSO representation is simplified as a controlled outlet, the resulting control is indeed very good; thus the internal MPC model is accurate enough for the purpose at hand. This may however not be the case for longer sampling intervals than 5 minutes where the internal MPC model is also less frequently initialized with HiFi model results. Currently, extension of the MPC framework is being investigated to better represent overflows in the internal MPC model. The performance of the current study is inherently difficult to compare with other control studies (such as for example Fiorelli et al., 2013) due to differences in control objectives, system layouts, applied rain events, means of evaluation, etc. as it is often the case for real time control studies (Lund et al., 2018). It is, however, clear from especially Figure 6 that the performance evaluation should be based on a range of rain events in order to describe the change in MPC performance as a function of baseline overflow volume, and that the MPC performance is highly dependent on the applied prediction horizon.

In this simulated proof-of-concept study, the optimized control actions from the MPC were transferred to the HiFi model which both acted as simulated truth and as real-time model for initialization of the internal MPC model. The cloudburst infrastructure has not yet been constructed. In this study, it was therefore not possible, but also not important, that the

HiFi model replicates reality in detail. In an operational setting, the internal MPC model is updated from real-time observations of the system and from the HiFi model, which should preferably continuously be updated using data assimilation. In the current study, the HiFi model was furthermore used to generate input to the MPC optimization offline prior to running the MPC. In an operational setting, the input model will however need to produce new flow forecasts at each sampling interval as illustrated in Figure 2, which calls for a fast, simplified input model such as the one proposed in Borup et al. (2017) and Thrysøe et al. (2019). This would reduce the computational burden but also the quality of the forecast and thus also of the control. This reduced forecast quality can however be diminished by assimilating system measurements into the input models (Lund et al., 2019b). The quality of the forecasts would further be reduced by using real rain forecasts. Only few papers compare the effect of using perfect versus estimated rain forecasts (for example, Fiorelli and Schutz, 2009; Fiorelli and Schutz, 2013; Löwe et al., 2016), and these generally obtain different performance reductions due to the use of different rain estimation methods (Lund et al., 2018). There is, as such, no lower limit to the quality of rainfall forecasts, and it is close to impossible to quantify what is a typical or relevant uncertainty on these. Therefore, we have chosen to focus only on perfect forecasts in the current study. Before an actual control implementation it would, obviously, be wise to make a thorough investigation of the impact of these uncertainties for the specific case.

5 Conclusions

In this study we elaborate on the possibility to dynamically activate above-ground cloudburst management solutions (green and grey infrastructure) to convey and store stormwater in situations where CSO to receiving waters otherwise seems inevitable. MPC was used to close and open stormwater inlets and to control a pump to empty a retention space. The MPC thus determined whether stormwater was kept on the surface or was allowed to enter the underground sewer system (integrated stormwater inflow control), and values in-between on/off and open/closed could be chosen. We conducted a simulated proof-of-concept study using a small catchment in Copenhagen with a cloudburst road and a retention space embedded in an area served by a combined sewer system with one CSO structure. We tested an MPC scenario with a sampling interval of five minutes, a setting duration of one minute and prediction horizons between 10 and 120 min. The MPC was compared to a baseline with no control (all stormwater entered the sewer system) and a maximum CSO reduction scenario (no stormwater entered the sewer system), all evaluated for 18 overflow events and 14 non-CSO-producing events in 2016 using a state-of-the-art hydrodynamic HiFi model as the ‘simulated truth’.

MPC of stormwater inflows significantly reduced the number and volume of CSOs if the prediction horizon was longer than the transport time in the pipe system (18.3 min). Increasing the horizon from 30 min to 120 min increased the annual CSO reduction from 9.9% to 12.4%, which corresponds to 78.6% to 98.4% of the maximum annual CSO reduction of 12.6%. This also increased the amount of completely avoided CSO events in 2016 from two to four. In no instance did the inclusion of integrated stormwater inflow control provoke a CSO when there was no CSO in the baseline. The MPC however kept water on the surface for one event that would not have resulted in a CSO, because the CSO structure in the internal MPC model was deliberately sized 5% smaller than its actual physical volume, as a ‘safety factor’ to compensate for internal model simplification errors. Removing the safety factor eliminated unnecessary water on the surface, but the number of avoided CSOs dropped from four to one for a prediction horizon of 120 min, and the annual reduction decreased to 12.0%.

Computational efficiency is the key reason for using a linear internal MPC model and formulating the optimization as a quadratic programming problem, as this allows for the expansion of the controllable area and/or inclusion of more optimization variables. Our results showed that the concept is compatible with the time constraints in an operational setting, and it is even possible to decrease the sampling interval or expand the controllable area.

Overall, we obtained near-optimal results with the MPC implementation. These results were produced using historical rain data as forecasts (ex-post forecast analysis) and the uncertainty related with real rain forecasts may lead to worse results. Simple CSO reduction was used as the operational goal, but the concept can be expanded to take other objectives into account. Once the practical aspects of dynamically controllable stormwater inlets, downspouts and other stormwater inflow pathways have been solved, we are confident that integrated stormwater inflow control, which utilizes the synergy between above-ground grey-green infrastructure and the underground sewer system can be an important element in making cities more water-smart and improving both the human and environmental health.

Acknowledgments and Data

This study was supported by Realdania through the “Klimaspring” program as part of the “Smart Cities Water Solutions” project, and by Innovation Fund Denmark through the “Water Smart Cities” project. We thank HOFOR for the HiFi model and Anne Katrine Falk and Rasmus Halvgaard (DHI) for many inspiring discussions and help with MIKE OPERATIONS. The data and models used in this research are commercial or confidential. We refer other researchers to contact HOFOR (for access to the HiFi model), the Danish Meteorological Institute (for access to the rain data), and DHI (for licenses to the MIKE software).

References

- Borup, M., Thrysoe, C., Arnbjerg-Nielsen, K., Righetti, F., & Mikkelsen, P.S. (2017). A fast surrogate model tailor-made for real time control. *In Proceedings of the 14th International Conference on Urban Drainage*, Prague, Czech Republic, 1–4.
- Carr, R.W., Esposito, C., & Walesh, S.G. (2001). Street-surface storage for control of combined sewer surcharge. *J. Water Resour. Plan. Manag.*, 127(3), 162–167. doi:10.1061/(ASCE)0733-9496(2001)127:3(162).
- City of Copenhagen (2015). *Climate change adaptation and investment statement – Part 1*. Copenhagen, Denmark.
- DHI (2016a). *MIKE URBAN. Collection System*. Hørsholm, Denmark.
- DHI (2016b). *MIKE OPERATIONS. Documentation*. Hørsholm, Denmark.
- Eggimann, S., Mutzner, L., Wani, O., Schneider, M.Y., Spuhler, D., Moy De Vitry, M., Beutler, P., & Maurer, M. (2017). The potential of knowing more: A review of data-driven urban water management. *Environ. Sci. Technol.*, 51, 2538–2553. doi:10.1021/acs.est.6b04267.
- Fiorelli, D., & Schutz, G. (2009). Real-time control of a sewer network using a multi-goal objective function. *In Proceedings of the 17th Mediterranean Conference on Control and Automation*, Thessaloniki, Greece, 676–681. doi:10.1109/MED.2009.5164621.
- Fiorelli, D., Schutz, G., Klepiszewski, K., Regneri, M., & Seiffert, S. (2013). Optimised real time operation of a sewer network using a multi-goal objective function. *Urban Water J.*,

10(5), 342–353. doi:10.1080/1573062x.2013.806560.

Fletcher, T.D., Shuster, W., Hunt, W.F., Ashley, R., Butler, D., Arthur, S., Trowsdale, S., Barraud, S., Semadeni-Davies, A., Bertrand-Krajewski, J.-L., Mikkelsen, P.S., Rivard, G., Uhl, M., Dagenais, D., & Viklander, M. (2015). SUDS, LID, BMPs, WSUD and more – the evolution and application of terminology surrounding urban drainage. *Urban Water J.*, 12(7), 525–542. doi:10.1080/1573062X.2014.916314.

Fowler, A.M., & Hennessy, K.J. (1995). Potential impacts of global warming on the frequency and magnitude of heavy precipitation. *Nat. Hazards*, 11, 283–303. doi:10.1007/BF00613411.

García, L., Barreiro-Gomez, J., Escobar, E., Téllez, D., Quijano, N., & Ocampo-Martinez, C. (2015). Modeling and real-time control of urban drainage systems: A review. *Adv. Water Resour.*, 85, 120–132. doi:10.1016/j.advwatres.2015.08.007.

Gelormino, M.S., & Ricker, N.L. (1994). Model-predictive control of a combined sewer system. *Int. J. Control*, 59(3), 793–816.

Jørgensen, H.K., Rosenørn, S., Madsen, H., & Mikkelsen, P.S. (1998). Quality control of rain data used for urban runoff systems. *Wat. Sci. Tech.*, 37(11), 113–120.

Kabisch, N., Frantzeskaki, N., Pauleit, S., Naumann, S., Davis, M., Artmann, M., Haase, D., Knapp, S., Korn, H., Stadler, J., Zaunberger, K., & Bonn, A. (2016). Nature-based solutions to climate change mitigation and adaptation in urban areas: perspectives on indications, knowledge gaps, barriers, and opportunities for action. *Ecol. Soc.*, 21(2). doi:10.5751/ES-08373-210239.

Kerkez, B., Gruden, C., Lewis, M., Montestruque, L., Quigley, M., Wong, B., Bedig, A., Kertesz, R., Braun, T., Cadwalader, O., Poresky, A., & Pak, C. (2016). Smarter stormwater systems. *Environ. Sci. Technol.*, 50, 7267–7273. doi:10.1021/acs.est.5b05870.

Leth, C., & Christensen, P. E. (2016). *Cloudburst valve*. Denmark: Patent og Varemærkestyrelsen.

Li, H., Ding, L., Ren, M., Li, C., & Wang, H. (2017). Sponge city construction in China: A survey of the challenges and opportunities. *Water*, 9, 594. doi:10.3390/w9090594.

Löwe, R., Vezzaro, L., Mikkelsen, P.S., Grum, M., Madsen, H. (2016): Probabilistic runoff volume forecasting in risk-based optimization for RTC of urban drainage systems. *Environ. Mod. Softw.*, 80, 143–158. doi: 10.1016/j.envsoft.2016.02.027.

Lund, N.S.V., Borup, M., Madsen, H., Mark, O., Arnbjerg-Nielsen, K., & Mikkelsen, P.S. (2019a). Integrated stormwater inflow control for sewers and green structures in urban landscapes. *Nat. Sustain*, 2, 1003–1010.

Lund, N.S.V., Falk, A.K.V., Borup, M., Madsen, H., & Mikkelsen, P.S. (2018). Model predictive control of urban drainage systems: A review and perspective towards smart real-time water management. *Crit. Rev. Environ. Sci. Technol.*, 48(3), 279–339. doi:10.1080/10643389.2018.1455484.

Lund, N.S.V., Madsen, H., Mazzoleni, M., Solomatine, D., & Borup, M. (2019b). Assimilating flow and level data into an urban drainage surrogate model for forecasting flows and overflows. *J. Environ. Manage.*, 248(109052), 1–13.

Madsen, H., Falk, A.K., & Halvgaard, R. (2018). A model predictive control framework for real-time optimisation of water system operations. *In Proceedings of the 13th International Conference on Hydroinformatics*, Palermo, Italy, 3, 1281–1288.

- Madsen, H.M., Brown, R., Elle, M., & Mikkelsen, P.S. (2017). Social construction of stormwater control measures in Melbourne and Copenhagen: A discourse analysis of technological change, embedded meanings and potential mainstreaming. *Technol. Forecast. Soc. Change*, 115, 198–209. doi:10.1016/j.techfore.2016.10.003.
- McHarg, I.L. (1969). *Design with nature*. New York, US: Doubleday/Natural History Press.
- MOSEK (2018). <https://www.mosek.com>. License retrieved 7/3, 2018.
- Nakai, E.H., & Carr, R.W. (1993). Urban stormwater runoff control system, village of Skokie, Illinois. In *Proceedings of the 20th Anniversary conference of ASCE's Water Resources Planning and Management Division*, Seattle, Washington, US, 758–761.
- Rosenzweig, B. , Ruddell, B.L., McPhillips, L., Hobbins, R., PcPhearson, T., Cheng, Z., Chang, H., Kim, Y. (2019): Developing knowledge systems for urban resilience to cloudburst events. *Environ. Sci. Policy*. 99, 150-159. doi.org/10.1016/j.envsci.2019.05.020.
- Schütze, M., Campisano, A., Colas, H., Schilling, W., & Vanrolleghem, P.A. (2004). Real time control of urban wastewater systems – where do we stand today? *J. Hydrol.*, 299, 335–348. doi:10.1016/j.jhydrol.2004.08.010.
- Sunyer, M.A., Gregersen, I.B., Rosbjerg, D., Madsen, H., Luchner, J., & Arnbjerg-Nielsen, K. (2015). Comparison of different statistical downscaling methods to estimate changes in hourly extreme precipitation using RCM projections from ENSEMBLES. *Int. J. Climatol.*, 35, 2528–2539. doi:10.1002/joc.4138.
- Thorndahl, S., Einfalt, T., Willems, P., Ellerbæk Nielsen, J., Ten Veldhuis, M.C., Arnbjerg-Nielsen, K., Rasmussen, M.R., & Molnar, P. (2017). Weather radar rainfall data in urban hydrology. *Hydrol. Earth Syst. Sci.*, 21, 1359–1380. doi:10.5194/hess-21-1359-2017.
- Thrysoe, C., Arnbjerg-Nielsen, K., & Borup, M. (2019). Identifying fit-for-purpose lumped surrogate models for large urban drainage systems using GLUE. *J. Hydrol.*, 568, 517–533. doi:10.1016/j.jhydrol.2018.11.005.
- Walesh, S.G. (2000). *Street Storage System for Control of Combined Sewer Surcharge*. Contract No. 8C-R416-NTSX. Cincinnati, OH: US EPA.
- Walesh, S.G. and Esposito, C. (2004). Street surface storage for control of combined sewer surcharge. In *Proceedings of the 2004 World Water and Environmental Resources Congress: Critical Transitions in Water and Environmental Resources Management*, Salt Lake City, Utah, USA, 629–640.
- Zimmer, A., Schmidt, A., Ostfeld, A. and Minsker, B. (2015). Evolutionary algorithm enhancement for model predictive control and real-time decision support. *Environ. Mod. Softw.*, 69, 330-341. doi: 10.1016/j.envsoft.2015.03.005.
- Zimmer, A., Schmidt, A., Ostfeld, A. and Minsker, B. (2018). Reducing combined sewer overflows through model predictive control and capital investment. *J. Water Resour. Plann. Man.*, 144(2). doi: 10.1061/(asce)wr.1943-5452.0000879.