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The Impact of Blue-Green Infrastructure and Urban Area Densification on the Performance of Real-Time Control of Sewer Networks

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Key Points:

- Urban transitions are modeled to assess the effect on optimal control (RTC) efficacy
- Strong divergence from optimality was associated with SUDS implementation
- Long-term implementation of RTC should include a regular re-evaluation of the strategy

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Urban areas are constantly developing and thereby affect the local water cycle. Real-time control (RTC) strategies are used to operate urban drainage systems optimally during these transitions. This paper aims to develop a methodology to study the impacts of common gradual changes occurring in the urban environment (densification of the urban area and implementation of blue-green infrastructure), forming cumulative transitions, on the functioning of real-time optimization procedures. A new generic methodology, relying on a comprehensive evaluation strategy based on three indicators assessing the continued optimal performance of RTC was proposed. This methodology was applied to two urban drainage catchments in Eindhoven and Rotterdam using both probabilistic and projected transitional paths. Based on the results obtained it can be noted that the performances of the RTC procedures were not strongly affected by the modeled transitions although the relative performance compared to the maximum performance potential decreases significantly with the large-scale implementation of blue-green infrastructure, indicating that the revision of RTC procedures could improve the sewer system functioning further. The relative performance loss associated with the modeled transitions was higher for model predictive control compared to heuristic RTC procedures for one case study and vice versa for the other. Continuous re-evaluation of the RTC strategy is, therefore, an important but overlooked part of the implementation of RTC procedures.

1. Introduction

Urban drainage systems (UDS) are designed to convey wastewater and urban runoff away from populated areas to treat the water and increasingly to recover valuable resources from it. To prevent flooding during rainfall events, combined sewer overflows (CSOs) are installed to discharge the excess of combined wastewater and urban runoff (i.e., stormwater) into a receiving water body. These CSO events can negatively impact the receiving water quality (Owolabi et al., 2022) and can be highly persistent and long-lasting in nature, for example, as in the case of micro-pollutants from CSO events impacting water resources (Mutzner et al., 2022). These effects are projected to be exacerbated by more intense rainfall events resulting from climate change (Gogien et al., 2022) and the expansion and densification of the population in existing urban areas.

To minimize the adverse effects of CSOs, blue-green infrastructure in the form of sustainable urban drainage systems (SUDS) is increasingly implemented to revert to the pre-urbanized hydrological conditions by allowing more infiltration in the urban environment(Carter & Fowler, 2008). Allowing significant parts of the urban runoff to infiltrate or to be temporarily stored, alleviates pressure on the drainage system and can therefore significantly reduce the CSO volumes (e.g., Chen et al., 2019). Using these types of nature based solutions are increasingly mandated by legislative bodies. The new EU Urban Wastewater Treatment Directive, for example, explicitly states a preference for green developments and states that gray infrastructure should only be envisaged where absolutely necessary. In future (re)developments of the urban environment, different runoff patterns compared to the current situation are therefore highly likely.

Another increasingly popular option to reduce CSOs is the use of Real-Time Control (RTC) procedures. RTC relies on real-time data obtained from the UDS to optimally control the system actuators (pumps and moveable gates) which has the potential to improve the UDS performance by activating redundant storage capacity in the system (Schütze et al., 2004). Various methods have been developed to achieve this, and can broadly be defined as heuristic and real-time optimization control methods (Garcia et al., 2015). Heuristic control methods are usually in the form of rule-based control, where a set of (optimized) rules are defined offline and implemented online.

Real-time optimization, on the other hand, optimizes the setpoints of the UDS actuators at every time step (i.e., online) and can therefore dynamically react to unanticipated rainfall and other events. These methods are based on the use of simulation models which have been calibrated to accurately represent the dynamics of the UDS. This means that the control rules are based on a snapshot of an ever evolving urban environment. Changes to the surface of the urban environment, through densification or re-greening of the area, can alter the representativeness of the model and therefore impact the optimized settings or optimization function.

The combined implementation of RTC combined with SUDS has gained attention in recent years. This co-implementation can decrease CSO volumes more effectively compared to either strategy on its own (Altobelli et al., 2020). A heuristic-based framework for the co-implementation of RTC and SUDS was later devised and showed similar increased potential (Jean et al., 2021). In an extension of the framework, the implementation of real-time optimization methods in the form of model predictive control (MPC) in conjunction with SUDS showed further increased potential (Jean et al., 2022).

These RTC strategies were specifically designed with the implementation of new SUDS in mind. This assumes a high level of integration between urban developers and operators, which in practice has proved challenging (Manny, 2023; Nieuwenhuis et al., 2021). Furthermore, the deployment of SUDS in the urban environment might consider multiple criteria with the effect on the in-sewer hydrodynamics only forming a small part of the decision-making process (Donati et al., 2022; Seyedashraf et al., 2022). This recent shift is likely to further complicate the integration between urban developers and operators, potentially exacerbating the loss of UDS performance related to the RTC procedure. Additionally, a difference between the urban development planning and the final built environment might arise (Vollaers et al., 2021), affecting the UDS dynamics and thereby potentially the optimal RTC procedure.

Alongside the implementation of SUDS, (re-)densification within existing city limits to create compacter urban areas is a commonly observed transition around the world (Broitman & Koomen, 2015; Næss et al., 2020; Shahtahmassebi et al., 2016). Associated with an increase in the level of imperviousness in an urban environment, the increase in population is projected to increase the runoff loading of the UDS. An annual increase of around 0.5% in levels of imperviousness was reported (ranging from −0.1% to 0.9%) due to the densification of cities (Nowak & Greenfield, 2012). This increase in imperviousness will increase the local runoff rates, changing the local dynamics and thereby potentially the functioning of the implemented RTC strategy.

These long-term changes have previously been shown to have a significant effect on the functioning of wastewater treatment plants (WWTPs) and should be systematically considered in the design stage of the WWTPs (Dominguez & Gujer, 2006). However, the impact of long-term has not been studied for the operation of UDS, and understanding how the gradual change of the urban environment can alter the functioning of RTC procedures is one of the key questions for ensuring the successful implementation of RTC strategies (van der Werf et al., 2022). This paper aims to understand the longevity of real-time control strategies for UDS concerning gradual configurational changes happening in the urban environment.

2. Methodology

This section sets out the framework proposed to assess the impact of gradual changes arising from long-term urban area transitions on the efficacy of previously implemented real-time control strategies. Gradual changes are defined here as changes to the surface or subsurface in the urban environment that do not significantly alter the dynamics of that system (e.g., local conduit replacement, tiling of a garden, the addition of small-scale SUDS). The combination of these gradual changes aggregates over years to form the transitional paths in the system which, cumulatively, can have an impact on the in-sewer dynamics. Here, only above-surface gradual changes (small configuration changes following the nomenclature set out in van der Werf et al. (2022)) are considered in the urban transitions modeled, more specifically the densification of the urban environment and the implementation of SUDS. These changes are implemented in a model-based framework after the performance of the current RTC configurations is calculated. A schematization of the methodology can be found in Figure 1.

Section 2.1 sets out two methods used to generate the transitional paths to assess their impact on the used RTC procedure. One of the methods relies on a detailed implementation of the changes whereas the other follows a stochastic implementation of possible changes. Section 2.2 details the assessment methods used in the framework.

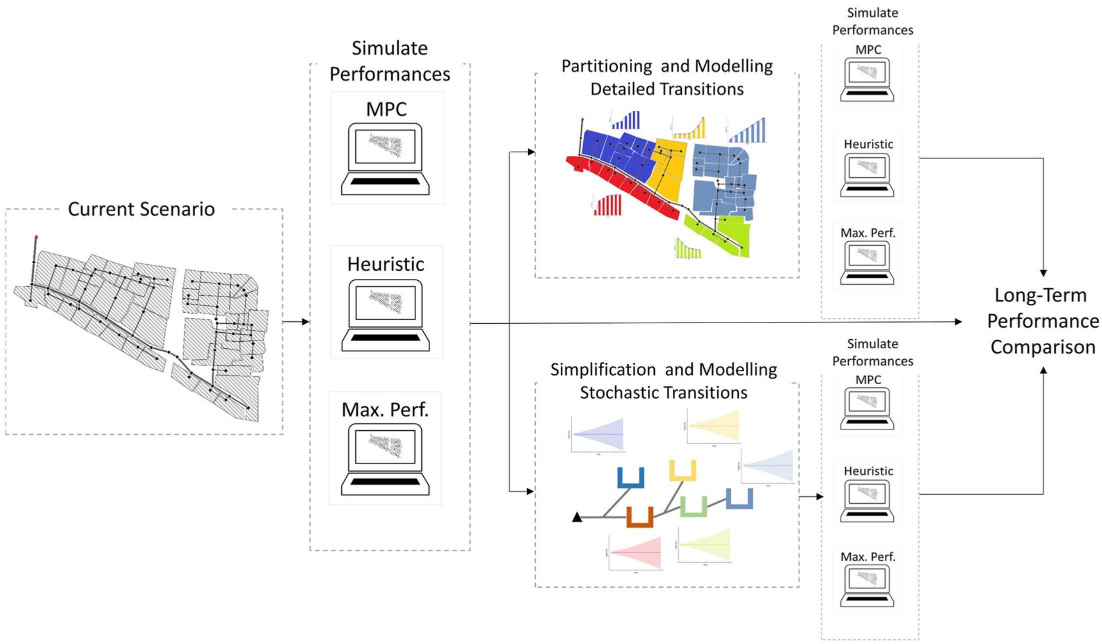

Figure 1. Schematization of the methodology presented here.

The case studies used to assess the longevity of RTC procedures, the details of the scenarios developed and the control procedures applied are detailed further in Section 3.

2.1. Urban Transitions

To generate future states of the UDS to be assessed, two methods for generating transitional paths have been used: (a) detailed implementation of the modeled urban transitions (based on a detailed full-hydrodynamic model, denoted here as detailed urban transitions) or using a (b) probabilistic, conceptual implementation of transitions (based on a conceptual model of the UDS, denoted here as stochastic urban transitions). The former allows for a more detailed assessment and the latter allows for stochastic analyses. The urban transitions assessed can be either based on planned changes to the UDS, to assess their relative impact, or exploratory modeling to understand the potential impacts of different transitions on the functioning of RTC procedures. Both methods are used to either generate scenarios to assess the impact of various urban transitions on the functioning of the RTC strategy, or to evaluate specific transitions which are considered for implementation. The former is used here and the exact scenarios generated following the transitions detailed below are detailed in Section 3.3.

2.1.1. Detailed Urban Transitions

A full-hydrodynamic model (FH) describes the virtual representation of the elements and dynamics of a UDS and allows for a detailed assessment of transitions happening within. FH models are computationally heavy, making random sampling of future states unfeasible. Assessing future scenarios should therefore follow a selective sampling form, such that the result allows for an inference of the relative impact of the analyzed transitions. This selective sampling can either be based on concrete plans or following a deviant case sampling structure (Draucker et al., 2007). Here we follow the latter as it highlights the potential impacts of urban transitions on the performance of RTC procedures.

Deviant case sampling refers to the sampling technique where extreme cases are used to further understand conditions, consequences, and interactions within a data set, making it a useful tool for cases where the number of possible simulations is limited. Here, deviant case sampling is used to make *N*-scenarios of which the impacts of RTC efficacy are assessed. To make these scenarios, the following steps are used: (a) UDS partitioning; (b) transitional definition; (c) scenario creation. These steps are outlined in more detail below.

The first step is to divide the UDS into sections, partitioning the sections based on the location of actuators (schematized in Figure 2), adjusted from the partitioning processes used for the design of a decentralized control

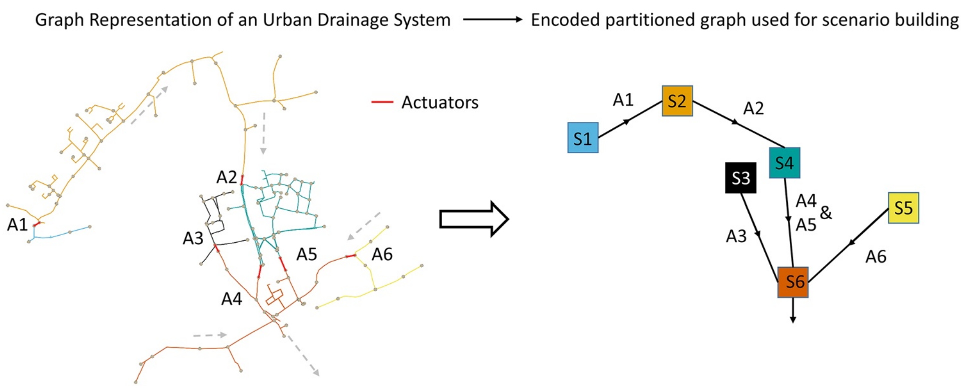

Figure 2. Schematic of the graph partitioning applied to an example Urban drainage systems. Arrows indicate flow directions.

scheme (Obando et al., 2022), though without the topological distinction. Considering the entire UDS as a graph $G = (V,E)$ where V represents the manholes and E the conduits in the UDS. The description of the above-ground sub-catchment linked to the nodes is encoded within V. All actuators are extracted from the set of nodes such that $A \subseteq E$ (highlighted links in red in the UDS shown in Figure 2). A partitioned graph is then formulated using A as the edges of the new graph following $G' = (V',A)$, where G' is the new, partitioned graph and V' is the set of nodes following $V' = \{S_1,S_2, \ldots,S_n\}$ where S_n is the set comprising of the conduits and nodes (including the encoded sub-catchments) for nth part contained by the actuators and the UDS boundaries (the simplified graph on the right in Figure 2). If part of the UDS is not clearly contained between actuators, due to multiple paths and loops within the UDS (as is the case of Section S4 in Figure 2), the non-contained sections are joined within a single set following $G' = (V',A^*)$, with A^* representing a subset of the set of actuators $A^* \subseteq A$ such that V' is fully contained. Here, this simplified model is then implemented in the EPA SWMM5 software (Rossman, 2015) using virtual reservoirs calibrated based on simulations from the full-hydrodynamic model as per van Daal-Rombouts et al. (2017).

In the second step, the gradual changes which underpin the transitional paths analyzed are defined. Although all types of gradual changes can be accommodated by the methodology, in this work, the implementation of SUDS and densification of the sub-catchment are considered. Changes to the conduits or nodes within the graph are therefore not included. For each sub-catchment in the catchment, the loss, degree of imperviousness, and size (as specified in the EPA SWMM5 software) are encoded in the model. These values are then changed per simulated timestep according to a predefined transition matrix, in which values are either pre-defined or a function of the current values (e.g., a decrease in relative densification for higher levels of imperviousness, where the rate depends on the current state).

In the third step, the scenarios used to generate the transitional paths to asses are defined following the deviant sampling principle, by only including system-wide changes that have the largest potential of changing the UDS hydrodynamic behavior. The scenario sampled should include maximum deviant cases from the current UDS (one scenario per transition studied, applying each proposed transition to all sections in the partitioned graph equally) and maximum heterogeneity cases (N scenarios with the largest difference between each section in the partitioned graph). Implementation examples of these scenarios are further detailed in Section 3.3.

2.1.2. Stochastic Urban Transitions

To allow for the sampling of a wider range of future scenarios, surrogate or conceptual models have to be used. Conceptual models used in urban drainage modeling are often virtual-reservoir models (Cembrano et al., 2004), but other forms of simplified models could be used (e.g., Dobson et al., 2022; Meijer et al., 2018), provided they incorporate a physical-based description of the UDS and its structure. This means an encoding of the effective surface area, UDS storage capacity, and pumping capacities (if appropriate). Here, the virtual-reservoir model was used, as the speed-up increased computational efficiency obtained this way allows for more simulations to be performed. Using this simplified model, the UDS is partitioned using the same graph partitioning algorithm used for the detailed transition analysis.

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Each subsection in the partitioned graph is changed using a pre-defined probability of change, following a stochastic sampling approach. The transitions in the stochastic framework are generated based on a Markov Chain-Monte Carlo (MCMC) approach, whereby the probability of a set of transitions occurring in the UDS depends on a pre-defined transitional matrix ΔS. The transitional matrix can be either pre-defined distribution or pre-defined functions (including distributed parameters) generating the new set of UDS characteristics. Different transitional matrices can be used, corresponding to different scenarios. Using this scenario-based MCMC approach, any urban transition projected (or combination of urban transitions) can be assessed.

Each chain in the MCMC approach consists of several steps. At each step, a new configuration of the UDS is generated. The performance of the heuristic control measure is then determined through the simulation of multiple rainfall events. The same set of rainfall events should be used to ensure the comparability of the results. This set of rainfall events should include only events that alter the RTC objective outcome (e.g., rainfall events that caused CSO events for a volume-based strategy). As the number of rainfall events used impacts the estimated RTC potential (van Daal et al., 2017), it is preferable to use as many events as possible. However, the computational penalty associated with more rainfall events is exacerbated as each event has to be run for every link in every chain in the computed MCMC simulations. A meaningful balance between the representativeness of the results and practical computational limitations should be reached and depends on the operators' preference.

This trade-off also makes the stochastic urban transitions practically only applicable to evaluate heuristic control procedures, as real-time optimization would be too time-consuming. To understand the potential impact of transitions on the performance of real-time optimization, one or more chains can be selected and assessed.

The set of rainfall events can include climate change projection, to assess the continued potential of RTC procedures under long-term, climate-related changes to the precipitation patterns. As the influence of climate change was assessed in previous work (Dirckx et al., 2018), this transition is omitted from this work, allowing a more detailed focus on the transitions which have not been studied before.

2.2. UDS Performance Assessment

The performance assessment part of the methodology is used to assess if an update of the RTC procedure is desirable or not. Information on both the UDS performance and the RTC procedure performance is needed to understand the impact of system transitions on the operation of the UDS. Three indicators are used: (a) total performance, (b) normalized performance, and (c) relative performance. The total performance is the outcome of the used objective function (e.g., the total CSO volume following a volume-based approach to RTC) for the evaluated rainfall events. The normalized performance is the ratio of the outcome of the used RTC objective function to the total loading into the UDS (e.g., the total CSO volume divided by the total rainfall depth following the same volume-based approach).

The relative performance of the UDS was previously determined through the means of a relative performance indicator (RPI) (van der Werf et al., 2021). This RPI is the ratio between the performance improvement compared to a static optimal baseline (optimized single input single output (SISO) heuristics rules for all actuators in the UDS) and the maximum potential performance improvement compared to this static optimal baseline following:

$$\mathrm{RPI}_a = \frac{J_{\mathrm{so}} - J_{\mathrm{RTC}}}{J_{\mathrm{so}} - J_{\mathrm{MTP}_a}} \tag{1}$$

where RPI_a is the RPI, J_{so} is the objective function outcome following the SISO procedure, J_{RTC} is the objective function outcome for the proposed RTC procedure and J_{MTP_a} is the absolute maximum theoretical performance of the current UDS layout.

The SISO rules are determined by having a threshold and set-point, the values for which are optimized through a formal optimization procedure, for each actuator in the UDS separately. The set-point is optimized, considering the physical constraints of the actuator, and bound between 0 and 1 (0 indicating no flow to pass through and 1 a fully open weir or pump). The optimization depends on the objective function, for which the total CSO volume is typically used. The maximum potential performance is the best performance achievable by any RTC procedure regarding the objective function (i.e., the minimum amount of CSO discharged for a volume-based approach). However, this formulation of the RPI cannot practically be applied here, as it requires the re-computation of the

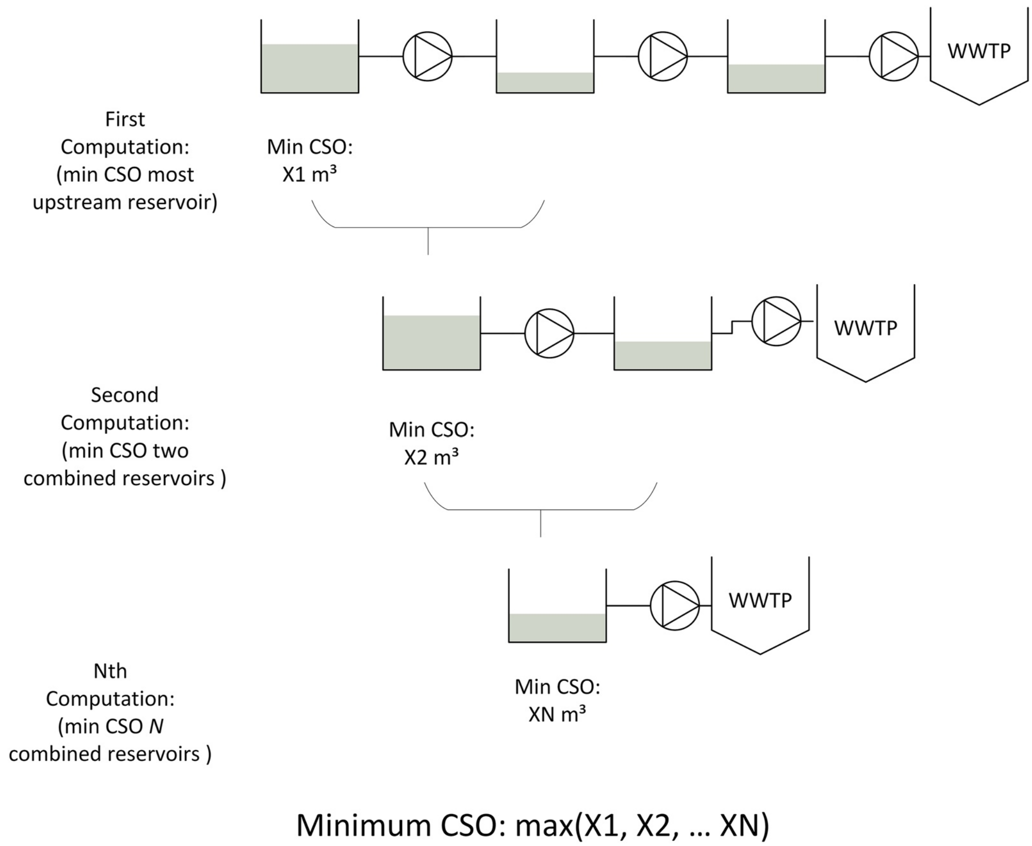

Figure 3. Overview of the adjusted central base approach to finding the minimum amount of combined sewer overflow.

static optimal settings per changed UDS. This is computationally too expensive because re-optimization of all generated scenarios within the stochastic framework would be necessary. Here, we define relative performance as the ratio between the RTC performance and the maximum RTC performance potential.

To compute the maximum theoretical performance, an adjusted version of the central basin approach (Einfalt & Stölting, 2002), better suited to partially pumped UDS, was previously proposed as part of the aforementioned RPI (van der Werf et al., 2021) and shown in Figure 3. This formulation considers every subsection of the UDS delimited by pumps as a single virtual reservoir model (see Gelormino & Ricker, 1994). For each cascading set of reservoirs (connected through pumps), the CSO volume for a given rainfall event is computed for the upstream-most modeled virtual reservoir. Then, this reservoir is combined with its downstream counterpart to form a new, combined virtual reservoir, and the CSO volume is computed for the same rainfall events. If the combined CSO volume is lower than the upstream-most virtual reservoir by itself, the latter is taken as the minimum CSO volume possible for the combination, as it is limited by the pumping capacity. This process is iteratively repeated until all the virtual reservoirs are combined into one. The final iteration then becomes the original formulation of the central basin approach. As this method considers the physical limits related to the pumping capacities in a UDS, it gives a more accurate representation of the maximum RTC potential, as following the central basin approach could overestimate this. In the case of multiple cascades within the UDS, each cascade is assessed individually and combined following the above-detailed procedure.

3. Case Studies

Two different urban drainage catchments were assessed here: the catchment connected to the WWTP Hoogvliet and part of the WWTP Eindhoven catchment, both situated in the Netherlands. These two catchments vary largely in their characteristics (size, number of actuators, presence of pumps). Using these two catchments allows for a wider investigation of the potential impact of transitions compared to using one, or similar UDS. Both catchments

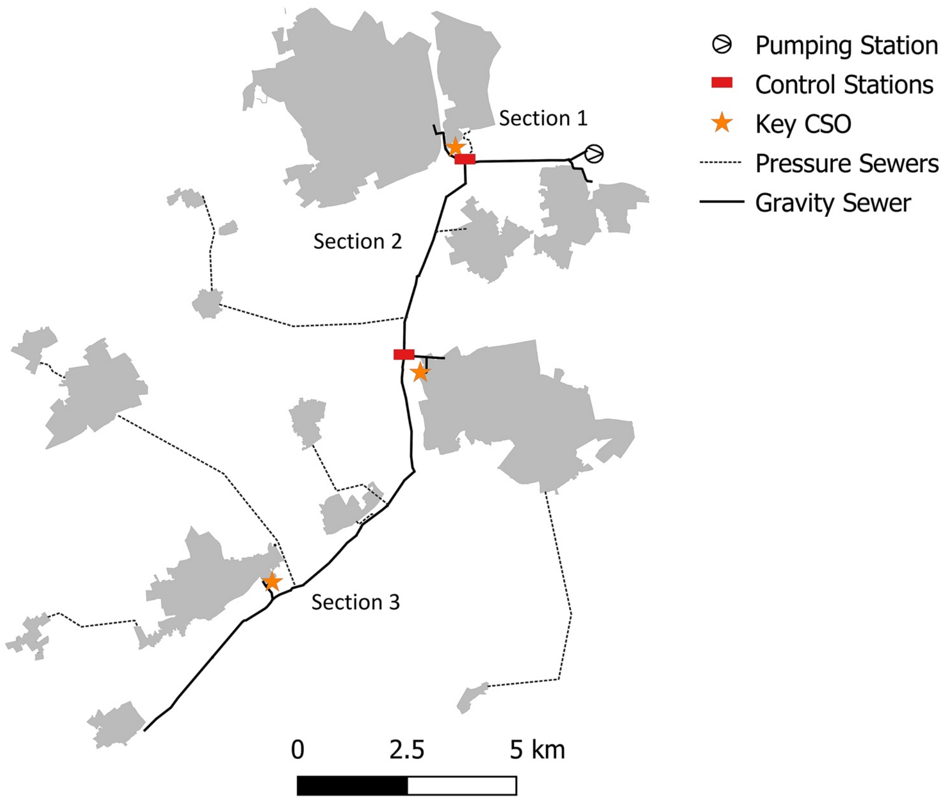

Figure 4. Overview of the Southern Sewer sub-system with three sections.

were modeled using the EPA SWMM5 (Rossman, 2015) and are controlled through the Python implementation PySWMM (McDonnell et al., 2020). In this section, the details of the Eindhoven catchment are given in Section 3.1, followed by the details of the WWTP Hoogvliet case in Section 3.2. The description of the transitions modeled are provided for each of the catchments as well and the rainfall details used are shown in Section 3.3.

3.1. Eindhoven Urban Drainage Catchment

3.1.1. Eindhoven Catchment Details

The urban drainage catchment discharging into the WWTP Eindhoven, with a total capacity of 750,000 p.e., stretches for 23 km in the east-west direction and 28 km in the north-south direction, servicing 10 municipalities. The catchment has been well documented in the control and modeling literature (Langeveld et al., 2013; Moreno-Rodenas et al., 2019). Three sub-systems discharge into the WWTP Eindhoven, the city of Eindhoven, Nueun-Son, and the Southern-Sewer. The focus of this work is the Southern-Sewer sub-system which consists of a large transport line where municipalities discharge into, either through gravity or pumped (Figure 4). Along the Southern-Sewer, a large pumping station (PS Aalst) with a capacity of 10,000 m^3/hr is situated, effectively splitting the UDS into two parts. In the part of the UDS upstream of PS Aalst, two control stations (CS Valkenswaard and CS De Meeren) are installed in the main transport sewer line (which has a total length of 18 km in this part of the UDS). These control stations can close the main sewer trunk and control the flow through a bypass with a moveable gate. This effectively creates three sections in the upstream part of the UDS. Each of these sections has a large CSO structure connected to it (see Figure 4). The UDS downstream of PS Aalst collects additional wastewater from surrounding municipalities before discharging into a treatment plant with a capacity of 750,000 p.e. (of which around 45% is reserved for the Southern-Sewer trunk). A full-hydrodynamic model and virtual-reservoir-based simplified model (here used as the internal-MPC model) of the catchment upstream of this pumping station were previously developed and calibrated (van der Werf et al., 2021). The full-hydrodynamic model consists of 10,500 nodes and 11,462 conduits, representing a UDS of approximately 427 km in total length. The total catchment area is 15.1 km^2 with an in-sewer storage capacity of around 6.7 mm and an additional 4.1 mm available in storage facilities. The total area is split up into 8.0, 4.4, and 2.7 km^2 for Sections 1–3 respectively (see Figure 4).

The virtual-reservoir-based simplified model models part of the transport sewer as in reality (see Figure 4), to mimic the delays and backwater effects experienced in the system. This modeling decision means that formal optimization using linear or quadratic programming methods is not possible, given the non-linear nature of the dynamics in this part of the sewer. Simplifying these dynamics would potentially lead to a loss of RTC efficacy due to increased uncertainties in the internal-MPC model (Castelletti et al., 2023; van der Werf et al., 2023). As any effect the transitions might have on the RTC efficacy is due to increasing model uncertainties, additional (significantly large) uncertainties could mask any effects of these transition-induced uncertainties. The virtual reservoirs were implemented in the EPA SWMM5 software. The aforementioned three main CSO structures in the UDS are indicative of the total CSOs load for each section of the Southern-Sewer sub-system and are therefore used as the reported CSO loads.

3.1.2. Real-Time Control for Eindhoven

A volume-based control strategy was set up for this catchment, aiming to reduce the total CSO volume discharged through the UDS. The associated objective function is as follows:

$$\min \sum\nolimits_{i=1}^{N} \sum\nolimits_{t=1}^{T} \mathrm{CSOvol}_{i,t} \tag{2}$$

where N is the number of CSO structures in the UDS, T is the number of times steps evaluated, and the $\mathrm{CSOvol}_{i,t}$ is the total CSO volume recorded (in m^3) at location i and time t. This minimization problem is subject to implicit constraints (flow and energy balance) which are encoded in the EPA SWMM software. Explicit constraints are added in the form of minimum opening (a value of 0 representing a fully closed orifice) and maximum opening (1 for a fully opened orifice) values. No other explicit constraints are added to the optimization function.

Three different RTC approaches were used here: RTC based on simple heuristics, RTC based on more advanced heuristic control, and an MPC-based RTC. The simple heuristics RTC strategy is based on a single set-point control procedure. Both control stations will limit flow when wet weather flow is detected (the downstream level is above a set threshold). Control Station de Meeren (the downstream most control station) has a target flow rate of 5,000 m^3/hr and Control Station Valkenswaard (the upstream most control station) has a target flow rate of 2,500 m^3/hr. The advanced heuristic-based RTC procedure computes the flow rate for each control station dependent on the state of the upstream and downstream section (filling, emptying, spilling, stable or dry weather flow), using an optimized lookup table to find a pre-defined set point for each combination of upstream and downstream state. and the optimized setpoints were determined and described in previous work (van der Werf et al., 2021) and the key definitions of the states and setpoints can be found in Supporting Information S1 (Tables S1–S3).

An MPC procedure was also set up (see Lund et al., 2018 for terminology used here). The MPC optimizes the setpoints of the two aforementioned control stations using the previously developed simplified model implemented in EPA SWMM5 (see van der Werf et al. (2021) for the details). Setpoints are optimized at five-minute intervals using the objective function shown in Equation 2, whilst considering the constraints mentioned above. The MPC architecture makes use of a Genetic Algorithm, as used by Sadler et al. (2019). This MPC architecture was previously used for the same catchment in van der Werf et al. (2023) and has showed to perform well for this catchment. A prediction horizon of 2 hr was selected, as this was the horizon for the rainfall nowcast data available. More specifically, an elitist Genetic Algorithm (Goldberg, 1989) was used to solve the aforementioned optimization problem over a control horizon of 1 hr, as it has been commonly done in RTC studies over the years (see e.g., Rauch & Harremoes, 1999 and Lund et al., 2018 for an overview), also in more recent MPC studies (Abou Rjeily et al., 2018; Li, 2020; Rathnayake & Anwar, 2019). The GA has been shown repeatedly to identify the near–global optimal solutions in relatively few iterations (Vasiliev et al., 2022). The set of GA parameters used can be found in Supporting Information S1 (Table S3a). If the GA reached the maximum number of iterations without improvement before the sampling interval, the obtained set points were assumed to be (near) optimal for that time interval. Other optimization methods from MPC literature, particularly quadratic and linear programming, were not used given the importance of the non-linear hydrodynamics in the transport sewer. As mentioned before, linearizing this part of the UDS would lead to an oversimplification of the dynamics in the internal-MPC model which can lead to a loss in the performance of the MPC procedure due to uncertainties (van

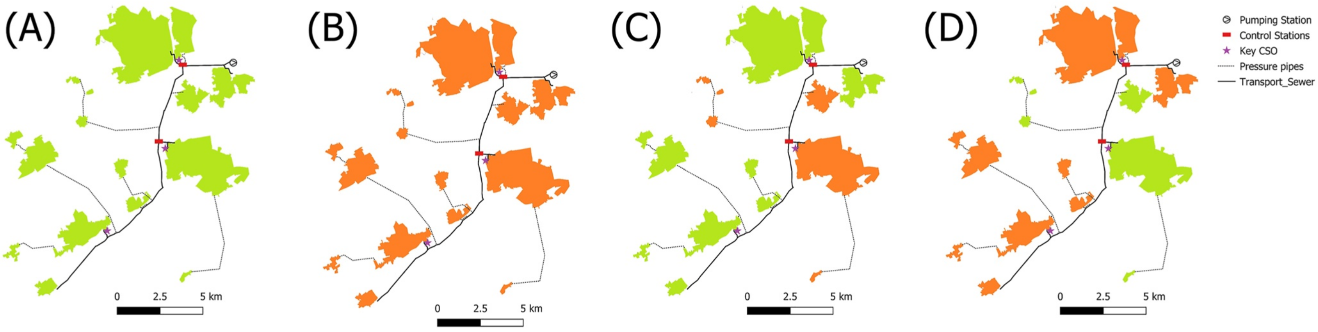

Figure 5. Graphical overview of the scenarios, orange denoting areas of densification and green denoting areas with increased sustainable urban drainage systems implementation. Panel (a) represents Scenario 1, (b) Scenario 2, (c) Scenario 3, and (d) Scenario 4.

der Werf et al., 2023). The optimization runs were performed on a desktop PC with a four-core Intel i5-6500 CPU @ 3.20 GHz. Following EPA SWMM5 internal code, the simulation time step is variable, with a minimum step of 5 s used for stability reasons.

3.1.3. Detailed Urban Transitions

Four scenarios were set up for the detailed transitions assessment for the WWTP Eindhoven catchment. The urban transitions were exclusively applied to the sub-catchments in the UDS, thereby changing the effective catchment size (either an increase through densification or a decrease through SUDS implementation). Scenario 1 increases the effective catchment size at the local scale where possible (following the rules set out in Section 2.1) for all the partitioned sections. Scenario 2 decreases the effective catchment sizes in all catchments (similarly following the rules set out in Section 2.1). Scenarios 3 and 4, on the other hand, combine densification and SUDS implementation, such that the difference between adjacent sections is the highest. Here, this results in an increase and decrease in the effective catchment sizes for the middle part and the other parts respectively (Scenario 3) and vice versa (Scenario 4). Figure 5 represents these scenarios visually.

Pre-defined annual changes were determined by projecting past trends (in the case of population growth) and assuming that the population increase is confined to the current UDS layout boundary. This equates to an annual densification rate of 0.4% (within the range that was reported earlier by Nowak and Greenfield (2012)). SUDS implementation is assumed to follow a linear decrease toward 0% runoff into the combined drainage system in 30 years (based on the current ambition of the Waterboard responsible for managing water quality in the catchment area). As this ambition will be achieved through both the disconnection of the combined sewer system and the implementation of SUDS, we assume that the latter will account for a 20% effective catchment size reduction. These annual changes were implemented and models were created for the UDS in 5 and 25 years.

3.2. WWTP Hoogvliet Urban Drainage Catchment

3.2.1. WWTP Hoogvliet Catchment Details

WWTP Hoogvliet is situated to the west of the city of Rotterdam, the Netherlands. It comprises five sewer districts separated into three individual inputs to the WWTP. All districts are pumped, with two cascading district lines (see Figure 6). CSOs can occur (in an uncontrolled manner) through CSO weirs discharging to urban canals, or in a controlled manner through pumped CSO discharging to the river *Nieuwe Maas*, which is ecologically less sensitive to CSO impacts compared to the urban canals making the reduction of CSO volume discharge here less important. A detailed overview of the UDS characteristics, including model details, is provided in Supporting Information S1 (Table S4). The model used is a set of virtual reservoirs connected through pumps, implemented in the EPA SWMM5 software.

3.2.2. Real-Time Control for WWTP Hoogvliet

A heuristic control strategy was developed for this catchment as part of the Central Automatic Control 2.0 (CAS2.0) project initiated by the municipality of Rotterdam (Langeveld et al., 2022). The objective of this control strategy is to prioritize the minimization of CSO volume released into the internal city canals. The minimization

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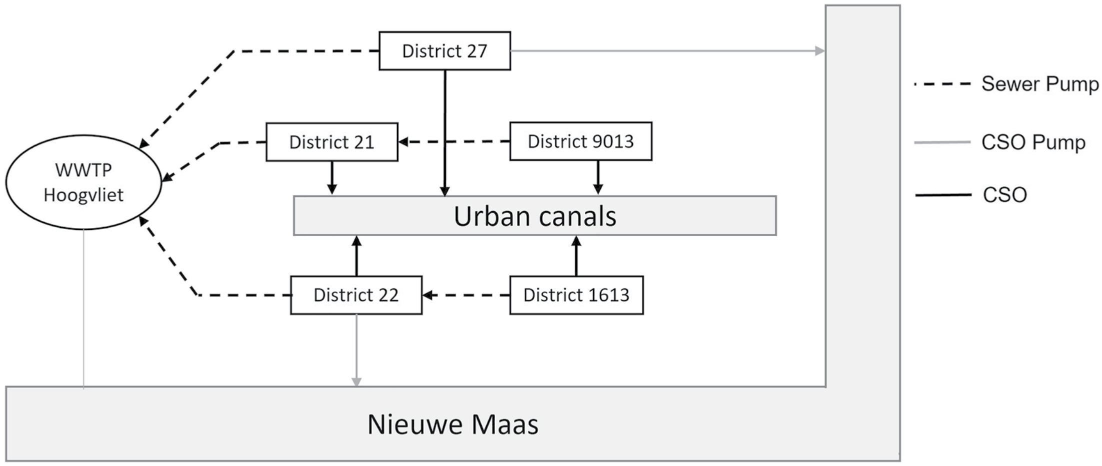

Figure 6. Schematization of the Hoogvliet catchment.

of the CSO volume discharged through the pumped CSO toward the Nieuwe Maas is of secondary importance, for the reason mentioned before. In practice, urban flooding is always prioritized over this, but not considered in this work as rain events causing flooding were not in the used analyzed data set. To achieve the aforementioned objective, the CSO pumps are switched on at 80% filling degree of the connected sewer districts and the pumping capacity to the treatment plant is decreased to not overload it (the total in-sewer pumping capacity exceeds the hydraulic treatment capacity). For example, if the filling degree of district 22 (see Figure 6) exceeds 80%, the pumping rate to the treatment plant is reduced to 50%, and the pumped CSO is switched on. This setting is applied until the filling degree is below 80%, then the pumped CSO is switched off and the pumping rate to the treatment plant is increased to 100%. A detailed overview of all rules can be found in Supporting Information S1 (Table S5). The rules are evaluated every 15 min, as physical constraints on the actuator changing speed are a practical limitation within the UDS.

An MPC implementation of the UDS was also made, following the same implementation as previously described for the Eindhoven case study. The objective function used for the minimization follows:

$$\min w_1 \times \sum_{n=0}^{N} \mathrm{CSOvol}_n + w_2 \times \sum_{i=0}^{I} \mathrm{CSOvol}_i \tag{4}$$

where w_1 is a dimensionless weight associated with the pumped CSO volumes (implemented here as 1), CSOvol_n is the total volume discharged to the Nieuwe Maas through CSO n, N is the number of CSOs discharging to the Nieuwe Maas, I is the number of CSOs discharging to the internal city canals, CSOvol_i is the total volume discharged to the internal city canals through CSO i and the w_2 is the dimensionless weight used for prioritizing these CSOs in the objective function (in this implementation, a value of 10 was chosen in line with earlier research on the same catchment (Geerse & Lobbrecht, 2002), who also applied a factor of 10 difference in the weighting between discharges to the Nieuwe Maas and the urban canals). The re-evaluation using the MPC procedure is done every 15 min, following the aforementioned reasons. The optimization function was subject to implicit constraints (flow and energy balances) encoded in EPA SWMM software. Explicit constraints in the upper and lower limit of the actuators (0 for pump off and 1 for the pump at full capacity) were added. Although a linear or quadratic form of optimisation could have been used by further simplification of the internal-MPC model, an elitist Genetic Algorithm was used for the optimization of the objective function. This was to, as much as possible, align the optimisation methodologies between the two catchments. The set of GA parameters can be found in Supporting Information S1 (Table S3b). A control and prediction horizon of 1 and 2 hr respectively were used in the optimization procedure.

3.2.3. Stochastic Transitions for WWTP Hoogvliet

Three scenarios were set up to test within the stochastic framework: Scenario 1 following unbiased transitions, Scenario 2 following biased densification, and Scenario 3 following biased SUDS implementation. The *unbiased*

Table 1
Transition Probabilities per Parameter and Scenario

Scenario	SWMM parameter	Units	Transition cause	Growth distribution
Scenario 1—Unbiased Transitions	Sub catchment imperviousness	%	Urban growth leading to densification	N(3, 1)
	Sub catchment imperviousness	%	Implementation of SUDS	N(−3, 1)
Scenario 2—Biased Densification	Sub catchment imperviousness	%	Urban growth leading to densification	N(6, 2)
Scenario 3—Biased SUDS	Sub catchment imperviousness	%	Implementation of SUDS	N(−6, 2)

transitions scenario follows an equal probability implementation of densification and SUDS within each catchment; *biased densification* has a proclivity for densification; and *biased SUDS* has a proclivity for SUDS implementation. Each follows a set of transition probabilities at each step in the chain which is independent of previous states (Table 1), forming the basis of the used MCMC framework. The densification and SUDS implementation follow randomly sampled values per catchment (independent of the change applied to the other catchments) in the UDS from a normal distribution for the transition probability. To have a sufficiently wide range of changes staying within the planned or historically observed changes, normal distributions with a mean of 3% or and standard deviation of 1% were used for Scenario 1, and a mean of 6% with a standard deviation of 2% for Scenarios 2 and 3 (either growth or shrinkage of the effective catchment size).

Following the above probabilities of change, 100 Markov chains, each consisting of 15 transitional links, were set up per scenario giving several samples in a similar range to previous work (Babovic & Mijic, 2019; Urich & Rauch, 2014). Each link was run for 9 rainfall events, using observed rainfall events causing CSO events in the current UDS configuration. This was deemed sufficient as it is in line with previously published work looking at RTC and UDS transitions (Jean et al., 2022).

To assess if the re-evaluation of both the MPC and heuristic procedure can improve the long term functioning of the UDS, additional analyses were performed for the last link of one of the generated chains (based on the 3rd scenario). For this link, the MPC procedure was run twice: once using the original model as the internal-MPC model and once using the transitioned model instead. Similarly, the heuristic procedure was re-assessed for this same chain. The previously optimized set-points were re-optimized for the new situation. The new set-points were compared to the old ones to assess if re-evaluation of the heuristic procedure is necessary. Furthermore, the difference in the distribution of the performance of the transitioned and original UDS based on varying the set-points was assessed to further highlight potential sensitivities of the heuristic RTC procedure to the urban transitions.

3.3. Rainfall Data

Radar rainfall data was used for both catchments. The rain gauge adjusted radar data set with a 1 × 1 km resolution at a five-minute interval was used (available at dataplatform.knmi.nl, Overeem et al., 2009). To assess the performance of the RTC procedures under the future scenarios defined in the previous section, multiple rainfall events, representative of the events that caused or were close to causing CSO events were selected. Fifteen rainfall events were selected for the assessment of the detailed transitions (Eindhoven case study), with total rainfall depth ranging from 5.8 to 38.7 mm (mean 17.56 mm) with max intensities ranging from 2.2 to 30.6 mm/hr. For the stochastics transitions (WWTP Hoogvliet case study), 9 events recorded between 2019 and 2021 were used with total rainfall depths of 14.82–22.4 mm ranging with a mean depth of 18.24 mm, and maximum intensity ranging from 5.48 to 30.76 mm/hr. For the MPC runs, the observed rainfall data was used as the rainfall prediction as well, to minimize potential impacts of uncertainties on the final outcome. This allows for a better analysis of the impact of the transitions on the performance of RTC.

4. Results and Discussion

This section sets out and discusses the results obtained. First, the results for the WWTP Eindhoven catchment, following the detailed transitions framework, are presented and discussed. In the end, the WWTP Hoogvliet, following stochastic transitions, case study results are presented.

4.1. Detailed Urban Transitions—Eindhoven

Given the transitions described in Section 3.3, a net increase in CSO volume compared to the current, non-transitioned UDS was observed for Scenarios 1 (an increase of the total effective catchment size over the entire UDS) and 4 (increase in Sections 1 and 2 of the case study, decrease in Section 2 of the effective catchment size). Conversely, a total CSO volume decrease was observed for the other two scenarios, in line with the total effective catchment size of the UDS (Figure 7). The performance ranking of the three, unchanged RTC approaches (simple heuristics, advanced heuristics, and MPC-based) remained constant throughout all the scenarios.

Considering the normalized CSO value for each scenario, no clear trends could be identified (Table 2). All control procedures remained relatively stable, indicating a near-linear correlation between the CSO reduction and the

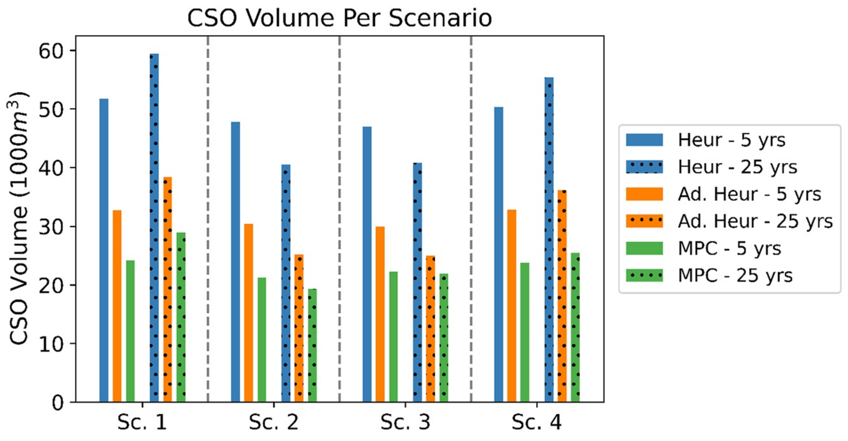

Figure 7. Total combined sewer overflow volumes for detailed transition scenarios, RTC approaches and projection horizons.

runoff reduction for the studied events, with no difference in dynamics found between the control producers. On the other hand, considering the relative CSO performance, a larger range in relative performance can be observed for the heuristic control (1.93–4.09) compared to the advanced heuristic (1.58–3.34) and MPC (1.44–2.98) procedures. Therefore, for this catchment, the simplest form of control (single-input single-output heuristics) is most sensitive to changes in the urban drainage system and catchment with the highest relative performance loss as it was the least able to materialize the RTC potential.

Considering the aforementioned change in the relative CSOs, the relation of these with the change in total generated runoff volume ($\Delta V = \frac{V_{\text{new}} - V_{\text{old}}}{V_{\text{old}}} * 100$) was investigated (Figure 8). Although no clear one-to-one relation between the total runoff change and the relative CSO volume could be observed, a negative correlation between the runoff change and relative CSO volume seems to arise, although no change with an increased runoff can be observed. Only considering the total runoff change is insufficient given the heterogenous implementation of the runoff change for scenarios 2 and 3. Especially the 25-year implementation of Scenario 3 (the data points highlighted in Figure 8), shows that total runoff change by itself does not sufficiently explain the variance in relative performance. However, additional data points are necessary to adequately distill the relations dictating the change in relative CSO volume.

Computing the comparative CSO volume (the total CSO volume for each scenario divided by the total CSO volume of the current UDS configuration for all three procedures), again no trend can be observed highlighting different levels of sensitivity to gradual changes occurring in the UDS between the three studied RTC approaches (Figure 9). MPC-based RTC approaches have been found to be relatively resilient against rainfall nowcast uncertainty (Fiorelli et al., 2013), and therefore indirectly to uncertainties in the rainfall-runoff module of the

Table 2
Results of the Detailed Urban Transitions

		Normalized CSO volume			Relative CSO volume		
Scenario	Transition year	Heuristic	Adv. Heur.	MPC	Heuristic	Adv. Heur.	MPC
Scenario 1	5	0.032	0.027	0.025	2.15	1.77	1.64
	25	0.034	0.026	0.025	2.13	1.66	1.54
Scenario 2	5	0.033	0.026	0.022	3.39	2.72	2.06
	25	0.031	0.022	0.020	4.09	3.34	2.98
Scenario 3	5	0.031	0.025	0.023	2.35	1.89	1.59
	25	0.026	0.022	0.020	3.69	3.09	2.74
Scenario 4	5	0.032	0.027	0.022	2.13	1.77	1.58
	25	0.032	0.026	0.022	1.93	1.58	1.44

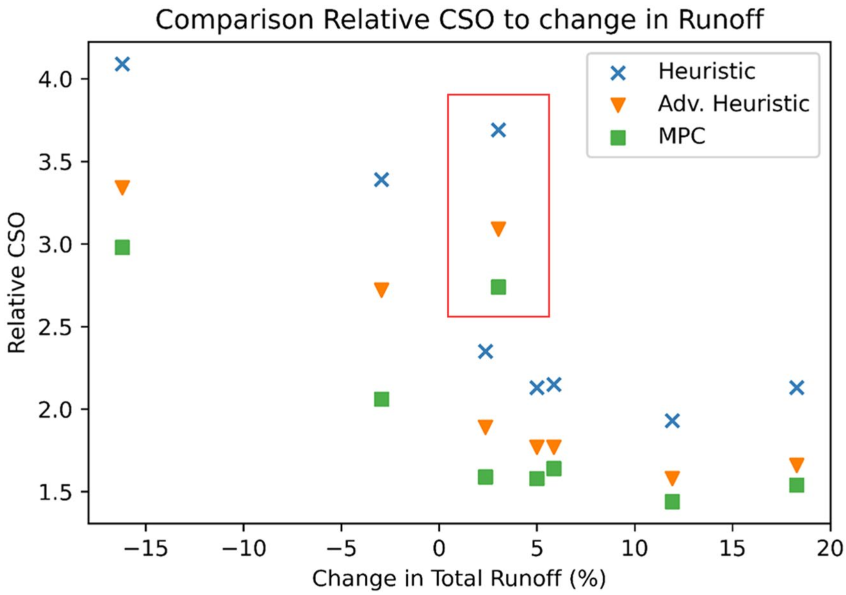

Figure 8. Difference in the relative combined sewer overflow change to runoff change per control procedure.

internal-MPC model (the part of the UDS that was changed here). The validity of the optimization method was checked by ensuring that the objective function achieved had leveled off completely and ensuring that the computational time to find the optimum was below the sampling period (5 min for the Eindhoven catchment).

4.2. Stochastic Urban Transitions—Hoogvliet

The impact of the urban transitions associated with the three scenarios on the total CSO volume was assessed for the WWTP Hoogvliet case study using an optimized heuristic control policy, optimized on the current state of the UDS. As the effective catchment size increases or decreases, the total CSO volume follows the same trend, as shown in Figure 10a. Similarly, the normalized CSO volume increases as the total CSO volume increases (Figure 10b). However, based on the relative performance, an opposite trend can be seen: there is a decreasing trend in relative CSO discharge associated with the increased effective catchment size (Figure 10c, note the difference in scale of the *y*-axis). Moreover, there is an increase of up to a factor of 40 in the relative CSO observed for Scenario 3 (biased SUDS). This indicates that the heuristic control procedure is unable to achieve the full RTC potential. This further highlights the need to consider all three metrics proposed here to gain a better understanding of the need for re-evaluating the control procedure.

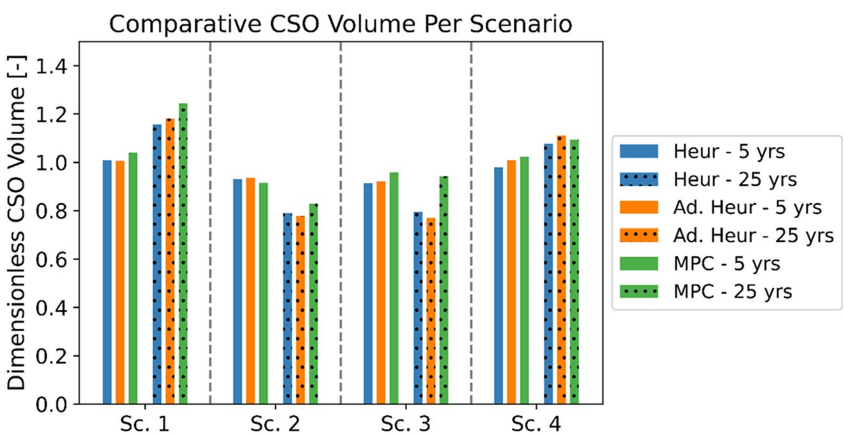

Figure 9. Ratio of the total combined sewer overflow (CSO) volume and the baseline CSO per event. No clear sensitivity between control types could be observed.

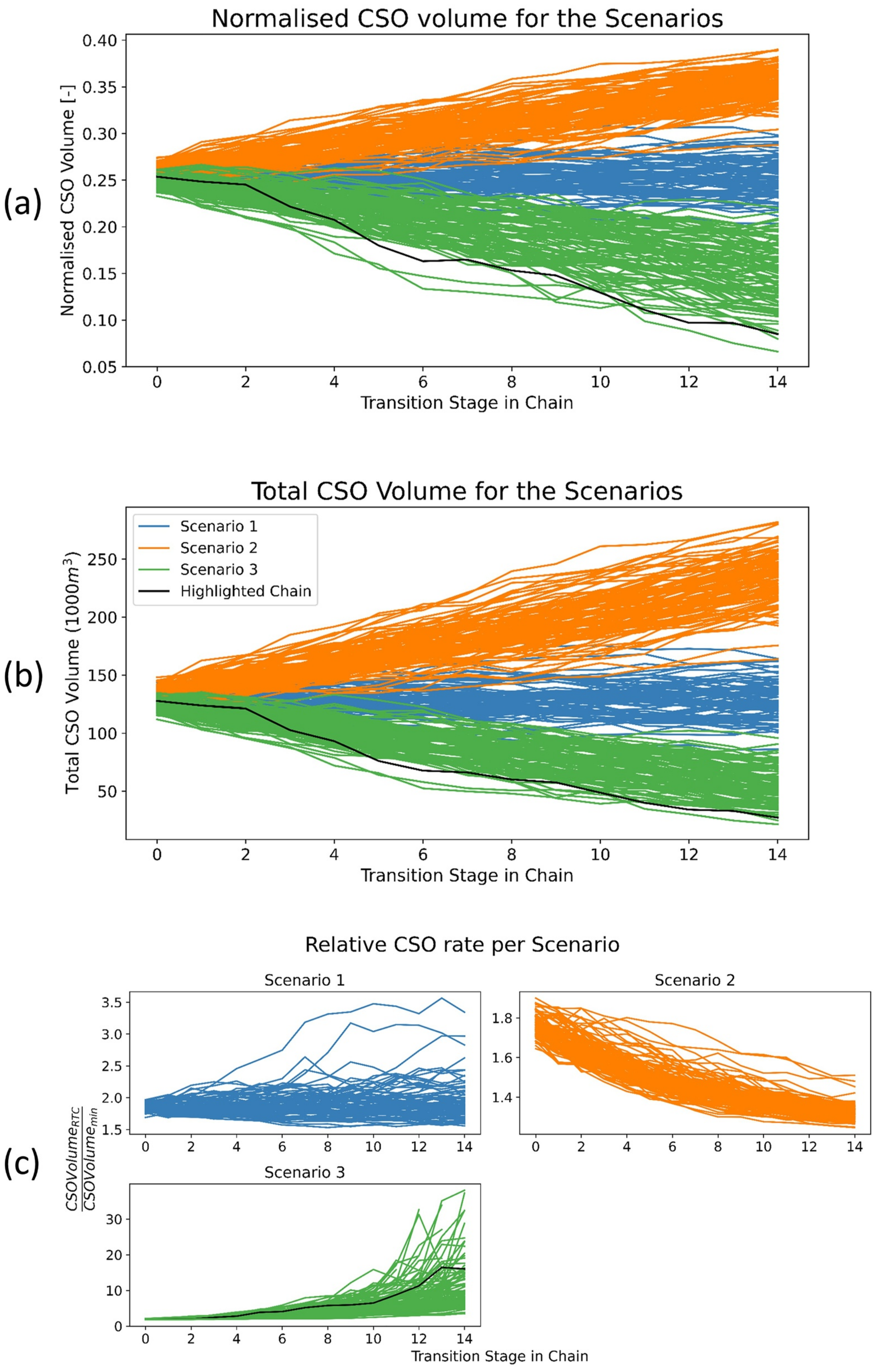

Figure 10. (a) Total combined sewer overflow (CSO) volume, (b) normalized CSO volume and, (c) Dimensionless Overflow rate per chain in each scenario.

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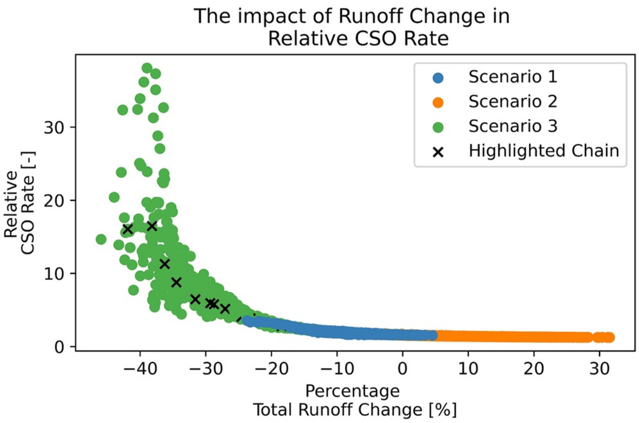

Figure 11. Assessment of the relation between percentage total runoff change and relative combined sewer overflow rate, based on 3 scenarios including 100 chains, with 14 links at 8 events per link.

To futher investigate the dynamics between a transitioning urban environment and the control procedure, one of the chains from stochastic Scenario 3 was selected for further analysis. The chain highlighted (Figure 10, Scenario 3) was selected as it showed one of the highest changes in total CSO volume and normalized CSO volume, yet more median relative performance, making it an interesting set of transitions to analyze.

The relationship with the percentage relative change in total generated runoff volume ($\Delta V = \frac{V_{\text{new}} - V_{\text{old}}}{V_{\text{old}}} * 100$) was investigated. A downward logarithmic relation between the relative CSO rate and the total runoff change was observed. As ΔV approaches -100% (meaning no runoff is generated and all the rainfall is captured by the implemented SUDS), the minimum CSO rate (the maximum RTC performance) will reach 0. The above indicator, in that scenario, is no longer useful, as the relative CSO rate goes to ∞ (as in theory all CSO events could have been negated). This can be seen in Figure 11, where the relation between the relative CSO rate and percentage runoff change becomes asymptotic around a 50% reduction in the total runoff on the left side of the figure. For the re-evaluation of the control rules, there is no clear breakpoint or threshold which can be identified as there is a relatively constant acceleration (similar to static hydrological impacts of urbanization as reported by Booth and Jackson (1997)). Around -15% total runoff change, however, the relative CSO rate exceeds 2.5 and starts to rapidly increase which would indicate a good point for re-evaluation. The logarithmic relationship does suggest that a more frequent re-evaluation of heuristic control policies is recommended.

The performance of the highlighted chain from Scenario 3 (see Figures 10 and 11) was further assessed to gain a better understanding of the performance of the various control procedures. Two MPC models were run to assess the importance of model recalibration: (a) using the original model (where no urban transitions were applied) and (b) using the model representing the transitioned state of the UDS as the internal MPC mode respectively, thus showing the RTC performance with and without recalibration of the internal MPC model. These two MPC implementations were compared to the original heuristic procedure (without re-optimizing the rules). The analysis was conducted for the same set of rainfall events as were used to assess the heuristic longevity (see Section 3.3 for details).

The total CSO volumes were caused exclusively by the pumped CSOs. However, the extent of the CSO volume varies significantly (Figure 12). The adjusted MPC performs the best with a total CSO volume of 17,519 m^3 (9.77 mm), followed by the heuristic control with a total CSO volume of 21,213 m^3 (11.83 mm), and finally the original MPC with a total CSO volume of 24,219 m^3 (13.51 mm). This means that the non-adjusted heuristic

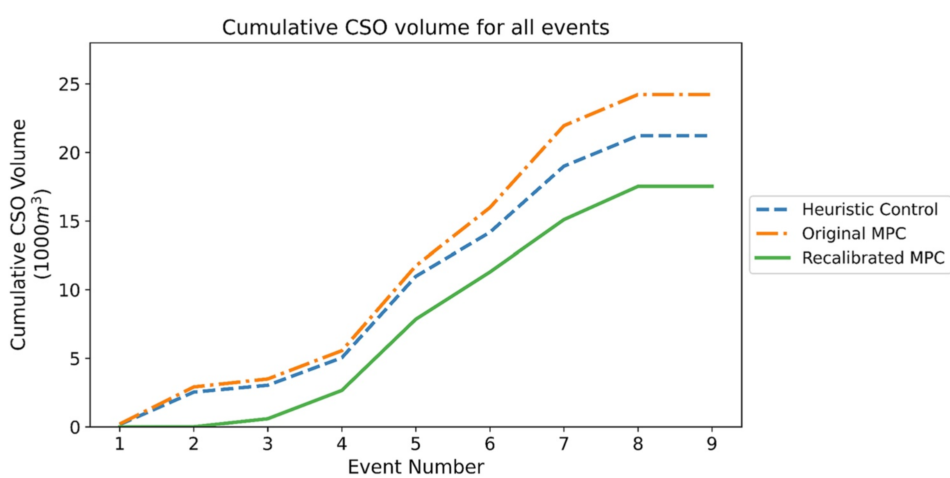

Figure 12. A comparison between the original model predictive control (MPC), recalibrated MPC and heuristic control for the final link in the highlighted chain (see Section 3.4 for rainfall details).

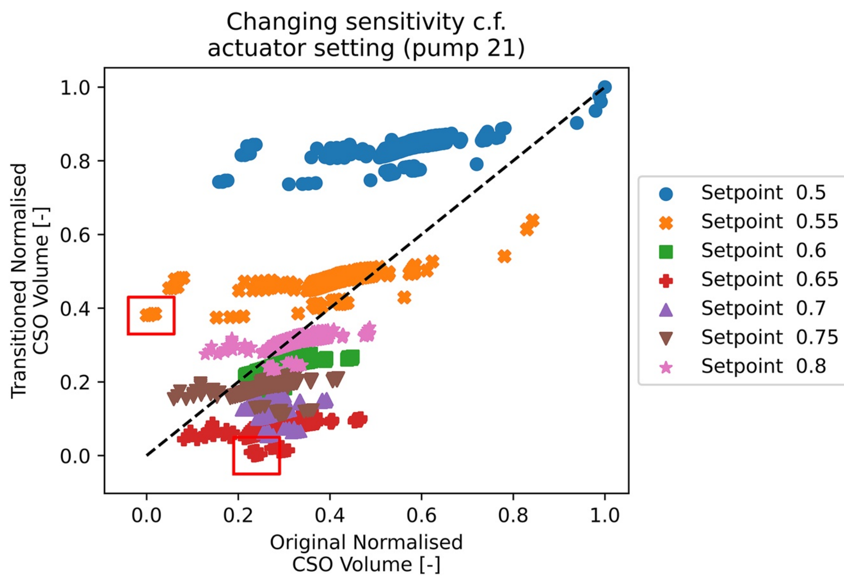

Figure 13. Difference in the sensitivity of the transitioned and original Urban drainage systems, showing the different potential set-points with regard to pumping station 21.

control outperformed the non-adjusted MPC procedure (Figure 12), which is the opposite of the sensitivity per procedure observed for the Eindhoven case study. Repeated re-evaluation of the performance of the internal MPC model used should be prioritized to maintain the long-term optimality of the MPC strategy. Continuous assessment of the predictive performance of the internal MPC model and its automatic recalibration should therefore be an integral part of the implementation of MPC strategies.

When considering the rebalancing of the heuristic control, some additional performance could be achieved when re-designing the control set-points. All control set points in the heuristic control were changed to find if there is a change in sensitivity to these set points in the procedure. For each set point, 7 new options were simulated (using the original set points and changing these set-points each with steps of −30%, −20%, −10%, 10%, 20%, and 30% (therefore covering a wide range of new options). This would mean that if a pumping station would have a capacity set-point of 50% in the current heuristic rules, the new situations evaluated were 50%, 55%, 60%, and 65% pumping capacity utility. If the current implemented rules were using either 0% or 100% of the capacity, the changes to the set-points were intervals of 5% (thus, from 0% to 35% and from 100% to 65%) The aim here was not to re-optimize the system, but to investigate if there was a change in the relative sensitivities of the system to the setpoints. Additionally, it was checked if a better solution existed within this new data set. The CSO volumes for the original (non-transitioned) and transitioned UDS were normalized based on their respective minimum and maximum outcomes. The events assessed were the same also those highlighted in Figure 12.

The changes in the heuristic set points lead to different dynamics in the normalized CSO volumes for the transitioned and original UDS (Figure 13). In this case, high variability is seen between the results of the different set points, exemplified by the dynamics of the settings of pump 21 in Figure 13. A positive coefficient of determination (0.61) was found between the two normalized CSO volumes, indicating that the relative sensitivity to the setpoints of the actuators has changed (if this wasn't the case the coefficient of determination would be closer to 1). For the set points analyzed, there was a lower level of variability found within the different setpoints for the transitioned UDS (indicated by the near horizontal clustering of the different setpoints) compared to the original UDS, indicating a relatively higher level of importance of this actuator in the RTC performance. This is a further indication that the dynamics within the UDS have sufficiently shifted to warrant re-optimization. Furthermore, the optimal heuristic set points have changed, as indicated by the red squares in Figure 13. The new set points mainly rebalance the system as the inflow patterns have changed locally, meaning the optimal flow ratios have changed accordingly. It should be noted, however, that his change in optimal solution could improve the system, but the improvement was comparatively low when considering the difference found for the re-evaluated MPC strategy: for the heuristic case, the new CSO volume became 20,198 m^3 (11.3 mm) for the assessed rainfall events. This is a 4.5% decrease in the CSO volume compared to the original heuristic rules, showing that

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some improvement is possible, though the effects are smaller compared to the MPC strategy. It should be noted, however, that this performance is not the optimized performance and that a complete overhaul of the design of the heuristic strategy might be needed for further optimisation.

This opposite level of sensitivity to change per procedure compared to the Eindhoven case study suggests a high level of case study specificity. This comparative difference in sensitivity is likely due to the nature of the heuristic control, where the Eindhoven case study relied on set points in the form of a set flow rate. In the WWTP Hoogvliet case, however, the main logic is on the activation and deactivation of pumps based on a single set-point and therefore of less influence on the overall UDS balance. The difference in performance for the WWTP Hoogvliet case as shown in Figure 12 was exclusively due to the pumped CSOs. The cause for the relative increase compared to the heuristic control is due to an overestimation in the runoff leading to the optimal setting calculated including the pre-amptive switching on of the pumped CSOs.This loss induced through the rainfall-runoff section of the internal MPC model is in apparent contrast with earlier findings of low levels of sensitivity to rainfall forecast uncertainty for MPC (Fiorelli et al., 2013; van der Werf et al., 2023). As the pumped CSOs cause overflows immediately when switched on, the self-adjusting properties of MPC (which are the cause for the low impact of rainfall forecast uncertainty on the performance of MPC methods) are less pronounced. Additionally, a relatively low frequency of set point updating (15 min due to physical constraints in the UDS) decreases the self-adjusting potential of the MPC scheme further.

4.3. Discussion

One of the key points highlighted by looking at the two case studies is the necessity to re-evaluate the applied RTC strategy when large-scale transitions occur in the urban environment, a time scale previously not considered in the review by Mollerup et al. (2016). This would require a shift in the current control paradigm, where the aim is to optimize a UDS in its current state as opposed to keeping the long-term changes in mind through the inclusion of performance tracking during the operation of the RTC strategies. Exploratory modeling techniques aimed at assessing possible pathways for urban water transitions (e.g., Duque et al., 2022) should explicitly consider the role of RTC as a means of accommodating these future transitions and the potential impacts the transitions may have on the performance potential of the corresponding RTC procedures.

Formal optimization techniques for network rehabilitation or SUDS implementation (e.g., Fiorillo et al., 2022) should also consider these interactions. As Digital-Twins are increasingly being experimented with in practice in the urban drainage community (Pedersen et al., 2021), the automated upkeep of these detailed models will become increasingly implemented. Incorporating the validation of the (relative) functioning current control procedures should therefore require comparatively less effort and has to be considered from the implementation of the control procedure. Furthermore, given the relative sensitivity of MPC-based RTC procedures to the transitions modeled here, future research into continuous data assimilation for the internal MPC model, similar to what is currently done for other hydraulic models (e.g., Milašinović et al., 2021) and for non-transitioning UDS (Hutton et al., 2014; Vermuyten et al., 2018), is recommended. The influence of data uncertainty, predominately the observed rainfall, might make the continuous data assimilation method difficult. Communication between the responsible parties for both the urban environment and the UDS operator should therefore be strengthened. The analysis done on the UDS as a socio-technical system (Manny, 2023) can be used for the identification of possible bottlenecks in this context.

Re-optimizing the heuristic-based RTC procedure to the changed boundary conditions has previously been used to re-establish improved function of the UDS after the implementation of both large-scale configurational changes (Seggelke et al., 2013; Zimmer et al., 2015) and small configurational changes (Altobelli et al., 2020; Jean et al., 2021). An exact moment at which the re-evaluation should take place cannot be asserted from the results obtained in this study and is case study specific. It likely depends on the UDS layout, actuators used in the UDS, heuristic-based RTC procedure, and the rate of urban transitions. Therefore, additional case studies are needed to investigate the relative impact of different UDS characteristics in this context.

Although a relatively high resilience to small changes in the UDS was found in this work, the rapid implementation of sponge cities (Nguyen et al., 2019) and ambitious governmental targets for runoff reduction can result in critical changes in the runoff pattern, requiring the re-optimizing of the heuristic RTC procedure. Continuous monitoring of the RTC performance and, equally important, the performance potential, is therefore critical for an implemented heuristic RTC procedure. A methodology for the identification of when the changes in the UDS are substantial enough to warrant the re-optimization of heuristic rules should be developed.

It should be noted that, in order to quantify the performance of different RTC strategies, multiple years of rainfall data should ideally be used (van Daal et al., 2017). However, the computational cost of MPC makes this practically impossible. Therefore, the exact impacts of the urban transitional scenarios developed here on the RTC performance cannot be assumed to be perfectly representative of the real change in performance associated with these scenarios. Still, the sensitivities to the transitions in the urban environment observed here are assumed sufficiently representative of the analyzed catchments as the range of rainfall characteristics used in the assessment ensures a relatively good representation of expected dynamics in the analyzed UDS. Validation of this assumption would strengthen further the conclusions presented here but the analyses conducted here are deemed sufficient enough to report the findings reported in this paper. For example, real radar data was used, ensuring heterogeneity in the spatial distribution of rainfall. Even if the total UDS capacity was exceeded, the potential for improvement through RTC could still be present by filling, distributing, and emptying the UDS in an optimized way. Using a set of rainfall events to quantify the CSO volume is preferable from a computational point of view, though it has been argued that continuous rainfall simulation can yield better results for the design of CSO solutions (Jean et al., 2018). As the aim of this work was to investigate if changes to the urban area can have a significant effect on the (relative) performance of RTC procedures, the use of a continuous rainfall modeling approach is recommended in future work.

Furthermore, the rainfall depth of various events was close to (falling under the limit and exceeding it) the combined pumping and static capacities of the two UDS. This type of rainfall event has frequently been shown to have the highest potential for performance improvement through RTC (Vezzaro, 2021). Possible effects of the urban transitions on the RTC performance were assumed highest for these events, as minor deviations from optimality can have relatively high impacts. However, no clear relation between the rainfall depth and the RTC performance loss was found within either of the datasets. This, in combination with the aforementioned apparent resilience against smaller UDS changes, was surprising as RTC procedures are designed and optimized to function as close to the UDS capacity as possible. This drift from optimality is clearly visible only when significant changes in urban permeability are realized, predominately due to the implementation of blue-green infrastructure.

Additional investigation of sensitivity of RTC strategies not considered here should also be done in future work. In this work, only rule-based RTC and MPC were considered. The sensitivity of distributed control procedures (e.g., Obando et al., 2022) or machine-learning based procedures (Tian et al., 2022) cannot be predicted based on the results obtained in this work, as the results were found to be RTC procedure specific.

5. Conclusions

This research presents a methodology for assessing the longevity of Real-Time Control (RTC) procedures in UDS. The new methodology was applied to two catchments in the Netherlands. The following transitional changes to the urban areas were studied: (a) densification of the existing catchments and (b) implementation of sustainable urban drainage systems (SUDS). These changes were studied based on a detailed representation of the UDS using deviant case sampling methods, and a simplified representation of the UDS using stochastic sampling strategies. Both heuristic and MPC based RTC procedures were evaluated. The performance of different RTC procedures under the modeled transitions was studied.

Based on the case studies results obtained the following conclusion can be drawn:

- The transitional changes in the analyzed urban areas start becoming significant, that is, impacting the performance of UDS RTC procedures (both heuristic and MPC), when changes to the total generated runoff reach approximately 15% or more. The impact is measured using both a measure of achieved RTC potential and RTC performance. This indicates a relatively high inherent longevity of both MPC and heuristic control procedures considering relatively slow transitions occurring in the urban environment;
- Regarding the relative sensitivities of heuristic and MPC-based control procedures, the results differed between the two case studies. Therefore, no generalized statements about the relative sensitivities of different RTC procedures could be made. The impacts of urban transitions should therefore be assessed separately for each UDS where RTC is currently implemented. In the UDS Hoogvliet case study, the long-term performance of real-time optimization started to deteriorate compared to the baseline heuristic method;
- To ensure the longevity of advanced RTC procedures, continuous monitoring of the performance of all control procedures is needed. This can avoid a loss in RTC performance in practice through the early identification

of these losses. Good communication between relevant stakeholders on both the urban design and operation sides should therefore be a key component in RTC implementation;

- Using the total CSO volume alone is not sufficient to assess the long-term performance of an urban drainage system operated through a volume-based control procedure. Volume rates alone do not provide sufficient insights into the change in RTC potential caused by urban transitions. Therefore, an additional metric based on the difference between the performance of the RTC strategy and the maximum RTC potential is needed to make informed decisions on the frequency of re-evaluations of the RTC procedure;
- A negative logarithmic relation between the reduction in total generated runoff and the relative RTC performance (measured by the ratio between RTC performance and the maximum RTC potential) was found for a heuristic RTC strategy implemented in the UDS Hoogvliet. This increasing performance loss when BG infrastructure is implemented on a large scale indicates the need to re-evaluate the underlying rules for heuristic control policies. Failing to account for the urban transitions would negate part of the gains made via BG infrastructure;
- Re-calibration of the internal MPC model can significantly improve the long-term performance of the RTC procedure. Automated data assimilation methods should therefore be included in future implementations of MPC procedures. This non-stationary approach to RTC could be a strategy to accommodate for urban transitions without the need for additional investments.

The conclusions presented here hold for the two case studies. Given the site-specific nature of the results, more case studies are necessary to predict correlations between urban transitions and their impact on RTC performance. Aside from this. future research directions should include additional transitions in the UDS, such as the ubiquitous implementation of separate sewer systems and changes to the (requirements of the) wastewater treatment plant. Especially changes to the underground infrastructure itself, or combined transitions, should be investigated. Furthermore, incorporating data assimilation techniques and automatic maintenance of full-hydrodynamic models in the continuous assessment framework should be prioritized to ensure the continued optimal performance of RTC procedures.

Data Availability Statement

Rainfall data used in this research is available from the KNMI website (dataplatform.knmi.nl). Models are the property of the relevant parties, and can be made available to readers only with the specific consent from those parties. Readers are encouraged to contact the corresponding author in order to start the data acquisition process. Figures in this work were made with Matplotlib, available under the licence https://matplotlib.org/. Models were made in the EPA SWMS 5 open source software, using the PySWMM python interface, available under the licence at https://www.pyswmm.org/citing. Furthermore, the SWMM API interface was used for interacting with the SWMM input files, using the MIT Licence at https://pypi.org/project/swmm-api/.

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References

Abou Rjeily, Y., Abbas, O., Sadek, M., Shahrour, I., & Chehade, F. H. (2018). Model predictive control for optimising the operation of urban drainage systems. *Journal of Hydrology*, *566*, 558–565. https://doi.org/10.1016/j.jhydrol.2018.09.044

Altobelli, M., Cipolla, S. S., & Maglionico, M. (2020). Combined application of real-time control and green technologies to urban drainage systems. *Water*, *12*(2), 3432. https://doi.org/10.3390/w12123432

Babovic, F., & Mijic, A. (2019). Economics evaluation of adaptation pathways for an urban drainage system experiencing deep uncertainty. *Water*, *11*(3), 531. https://doi.org/10.3390/w11030531

Booth, D. B., & Jackson, C. R. (1997). Urbanization of aquatic systems: Degradation thresholds, Stormwater Detection, and the limits of mitigation. *Journal of the American Water Resources Association*, *33*(5), 1077–1090. https://doi.org/10.1111/j.1752-1688.1997.tb04126.x

Broitman, D., & Koomen, E. (2015). Residential density change: Densification and urban expansion. *Computers, Environment and Urban Systems*, *54*, 32–46. https://doi.org/10.1016/j.compenvurbsys.2015.05.006

Carter, T., & Fowler, L. (2008). Establishing green roof infrastructure through environmental policy instruments. *Environmental Management*, *42*(1), 151–164. https://doi.org/10.1007/s00267-008-9095-5

Castelletti, A., Ficchi, A., Cominola, A., Segovia, P., Giuliani, M., Wu, W., et al. (2023). Model predictive control of water resources systems: A review and research agenda. *Annual Reviews in Control*, *55*, 442–465. https://doi.org/10.1016/j.arcontrol.2023.03.013

Cembrano, G., Quevedo, J., Salamero, M., Puig, V., Figueras, J., & Marti, J. (2004). Optimal control of urban drainage systems. A case study. *Control Engineering Practice*, *12*(1), 1–9. https://doi.org/10.1016/S0967-0661(02)00280-0

Chen, J., Liu, Y., Gitau, M. W., Engel, B. A., Flanagan, D. C., & Harbor, J. M. (2019). Evaluation of the effectiveness of green infrastructure on hydrology and water quality in a combined sewer overflow community. *Science of the Total Environment*, *665*, 69–79. https://doi.org/10.1016/j.scitotenv.2019.01.416

Dirckx, G., Korving, H., Bessembinder, J., & Weemaes, M. (2018). How climate proof is real-time control with regard to combined sewer overflows? *Urban Water Journal*, *15*(6), 544–551. https://doi.org/10.1080/1573062X.2017.1301499

Dobson, B., Watson-Hill, H., Muhandes, S., Borup, M., & Mijic, A. (2022). A reduced complexity model with graph partitioning for rapid hydraulic assessment of sewer networks. *Water Resources Research*, *58*(1). https://doi.org/10.1029/2021WR030778

Dominguez, D., & Gujer, W. (2006). Evolution of a wastewater treatment plant challenges traditional design concepts. *Water Research*, *40*(7), 1389–1396. https://doi.org/10.1016/j.watres.2006.01.034

Donati, G. F. A., Bolliger, J., Psomas, A., Maurer, M., & Bach, P. M. (2022). Reconciling cities with nature: Identifying local Blue-Green Infrastructure interventions for regional biodiversity enhancement. *Journal of Environmental Management*, *316*, 115254. https://doi.org/10.1016/j.jenvman.2022.115254

Draucker, C. B., Martsolf, D. S., Ross, R., & Rusk, T. B. (2007). Theoretical sampling and category development in grounded theory. *Qualitative Health Research*, *17*(8), 1137–1148. https://doi.org/10.1177/1049732307308450

Duque, N., Bach, P. M., Scholten, L., Fappiano, F., & Maurer, M. (2022). A simplified sanitary sewer system generator for exploratory modelling at city-scale. *Water Research*, *209*, 117903. https://doi.org/10.1016/j.watres.2021.117903

Einfalt, T., & Stölting, B. (2002). Real-time control for two communities—Technical and administrational aspects. In *Proceedings of the 9th international conference on urban drainage* (pp. 320–331). https://doi.org/10.1061/40644(2002)320

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 Journal*, *10*(5), 342–353. https://doi.org/10.1080/1573062X.2013.806560

Fiorillo, D., De Paola, F., Ascione, G., & Giugni, M. (2022). Drainage system optimization under climate change scenarios. *Water Resources Management*, *37*(6–7), 2465–2482. https://doi.org/10.1007/s11269-022-03187-0

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

Geerse, J. M. U., & Lobbrecht, A. H. (2002). *Assessing the performance of urban drainage systems: "General approach" applied to the city of Rotterdam* (pp. 199–209). Urban Water. https://doi.org/10.1016/S1462-0758(02)00017-1

Gelormino, M. S., & Ricker, N. L. (1994). Model-predictive control of a combined sewer system. *International Journal of Control*, *59*(3), 793–816. https://doi.org/10.1080/00207179408923105

Gogien, F., Dechesne, M., Martinerie, R., & Kouyi, G. L. (2022). Assessing the impact of climate change on Combined Sewer Overflows based on small time step future rainfall timeseries and long-term continuous sewer network modelling. *Water Research*, *230*, 119504. https://doi.org/10.1016/j.watres.2022.119504

Goldberg, D. E. (1989). *Genetic algorithm in search, optimisation and machine learning*. Addison-Wesley Publishing Co.

Hutton, C. J., Kapelan, Z., Vamvakeridou-Lyroudia, L., & Savić, D. (2014). Real-time data assimilation in urban rainfall-runoff models. *Procedia Engineering*, *70*, 843–852. https://doi.org/10.1016/j.proeng.2014.02.092

Jean, M. È., Duchesne, S., Pelletier, G., & Pleau, M. (2018). Selection of rainfall information as input data for the design of combined sewer overflow solutions. *Journal of Hydrology*, *565*, 559–569. https://doi.org/10.1016/j.jhydrol.2018.08.064

Jean, M. È., Morin, C., Duchese, S., Pelletier, G., & Pleau, M. (2021). Optimization of real-time control with green and grey infrastructure design for a cost-effective mitigation of combined sewer overflows. *Water Resources Research*, *57*(12). https://doi.org/10.1029/2021WR030282

Jean, M. È., Morin, C., Duchesne, S., Pelletier, G., & Pleau, M. (2022). Real-time model predictive and rule-based control with green infrastructures to reduce combined sewer overflows. *Water Research*, *221*, 118753. https://doi.org/10.1016/j.watres.2022.118753

Langeveld, J. G., Benedetti, L., De Klein, J. J. M., Nopens, I., Amerlinck, Y., Van Nieuwenhuijzen, A., et al. (2013). Impact-based integrated real-time control for improvement of the Dommel River water quality. *Urban Water Journal*, *10*(5), 312–329. https://doi.org/10.1080/1573062X.2013.820332

Langeveld, J. G., Liefting, H. J., Schoester, J., Schepers, J., & de Groot, A. C. (2022). Development and implementation of a large-scale real time control system: The Rotterdam case study. In *Proceedings of the international conference on urban drainage modelling*.

Li, J. (2020). A data-driven improved fuzzy logic control optimization-simulation tool for reducing flooding volume at downstream urban drainage systems. *Science of the Total Environment*, *732*, 138931. https://doi.org/10.1016/j.scitotenv.2020.138931

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. *Critical Reviews in Environmental Science and Technology*, *48*(3), 279–339. https://doi.org/10.1080/10643389.2018.1455484

Manny, L. (2023). Socio-technical challenges towards data-driven and integrated urban water management: A socio-technical network approach. *Sustainable Cities and Society*, *90*, 104360. https://doi.org/10.1016/j.scs.2022.104360

McDonnell, B. E., Ratliff, K., Tryby, M. E., Wu, J. J. X., & Mullapudi, A. (2020). Pyswmm: The Python interface to stormwater management model (SWMM). *Journal of Open Source Software*, *5*(52), 2292. https://doi.org/10.21105/joss.02292

Meijer, D., Van Bijnen, M., Langeveld, J., Korving, H., Post, J., & Clemens, F. (2018). Identifying critical elements in sewer networks using graph-theory. *Water*, *10*(2), 136. https://doi.org/10.3390/w10020136

Milašinović, M., Prodanović, D., Zindović, B., Rosić, N., & Milivojević, N. (2021). Fast data assimilation for open channel hydrodynamic models using control theory approach. *Journal of Hydrology*, *584*, 124661. https://doi.org/10.1016/j.jhydrol.2020.124661

Mollerup, A. L., Mikkelsen, P. S., Thornberg, D., & Sin, G. (2016). Controlling sewer systems – A critical review based on systems in three EU cities. *Urban Water Journal*, *14*(4), 435–442. https://doi.org/10.1080/1573062X.2016.1148183

Moreno-Rodenas, A. M., Tscheikner-Gratl, F., Langeveld, J. G., & Clemens, F. H. L. R. (2019). Uncertainty Analysis in a large-scale water quality integrated catchment modelling study. *Water Research*, *158*, 46–60. https://doi.org/10.1016/j.watres.2019.04.016

Mutzner, L., Furrer, V., Castebrunet, H., Dittmer, U., Fuchs, S., Gernjak, W., et al. (2022). A decade of monitoring micropollutants in urban wet-weather flows: What did we learn? *Water Research*, *223*, 118968. https://doi.org/10.1016/j.watres.2022.118968

Næss, P., Saglie, I., & Richardson, T. (2020). Urban sustainability: Is densification sufficient? *European Planning Studies*, *28*(1), 146–165. https://doi.org/10.1080/09654313.2019.1604633

Nguyen, T. T., Ngo, H. H., Guo, W., Wang, X. C., Ren, N., Li, G., et al. (2019). Implementation of a specific urban water management-Sponge City. *Science of the Total Environment*, *652*, 147–162. https://doi.org/10.1016/j.scitotenv.2018.10.168

Nieuwenhuis, E., Cuppen, E., Langeveld, J., & de Bruijn, H. (2021). Towards the integrated management of urban water systems: Conceptualizing integration and its uncertainties. *Journal of Cleaner Production*, *280*(2), 124977. https://doi.org/10.1016/j.jclepro.2020.124977

Nowak, D. J., & Greenfield, E. J. (2012). Tree and impervious cover change in U.S. cities. *Urban Forestry and Urban Greening*, *11*(1), 21–30. https://doi.org/10.1016/j.ufug.2011.11.005

Obando, G., Quijano, N., & OcampoMartinez, C. (2022). Decentralized control for urban drainage systems using replicator dynamics. *IEEE Access*, *10*, 56740–56762. https://doi.org/10.1109/ACCESS.2022.3177631

Overeem, A., Holleman, I., & Buishand, A. (2009). Derivation of a 10-year radar-based climatology of rainfall. *Journal of Applied Meteorology and Climatology*, *48*(7), 1448–1463. https://doi.org/10.1175/2009JAMC1954.1

Owolabi, T. A., Mohandes, S. R., & Zayed, T. (2022). Investigating the impact of sewer overflow on the environment: A comprehensive literature review paper. *Journal of Environmental Management*, *301*, 113810. https://doi.org/10.1016/j.jenvman.2021.113810

Pedersen, A. N., Borup, M., Brink-Kjær, A., Christiansen, L. E., & Mikkelsen, P. S. (2021). Living and prototyping digital twins for urban water systems: Towards multi-purpose value creation using models and sensors. *Water*, *13*(5), 592. https://doi.org/10.3390/w13050592

Rathnayake, U., & Anwar, A. F. (2019). Dynamic control of urban sewer systems to reduce combined sewer overflows and their adverse impacts. *Journal of Hydrology*, *579*, 124150. https://doi.org/10.1016/j.jhydrol.2019.124150

Rauch, W., & Harremoes, P. (1999). On the potential of genetic algorithms in urban drainage modelling. *Urban Water*, *1*(1), 79–89. https://doi.org/10.1016/S1462-0758(99)00010-2

Rossman, L. A. (2015). *Storm water management model user's manual, version 5.1*. National Risk Management Research Laboratory, Office of Research and Development, US Environmental Protection Agency.

Sadler, J. M., Goodall, J. L., Behl, M., Morsy, M. M., Culver, T. B., & Bowes, B. D. (2019). Leveraging open source software and parallel computing for model predictive control of urban drainage systems using EPA-SWMM5. *Environmental Modelling & Software*, *120*, 104484. https://doi.org/10.1016/j.envsoft.2019.07.009

Schütze, M., Campisano, A., Colas, H., Schilling, W., & Vanrolleghem, P. A. (2004). Real time control of urban wastewater systems—Where do we stand today? *Journal of Hydrology*, *299*(3–4), 335–348. https://doi.org/10.1016/j.hydrol.2004.08.010

Seggelke, K., Löwe, R., Beeneken, T., & Fuchs, L. (2013). Implementation of an integrated real-time control system of sewer system and waste water treatment plant in the city of Wilhelmshaven. *Urban Water Journal*, *10*(5), 330–341. https://doi.org/10.1080/1573062X.2013.820331

Seyedashraf, O., Battacin-Busolin, A., & Harou, J. J. (2022). A design framework for considering spatial equity in sustainable urban drainage infrastructure. *Sustainable Cities and Society*, *85*, 103960. https://doi.org/10.1016/j.scs.2022.103960

Shahtahmassebi, A. R., Song, J., Zheng, Q., Blackburn, G. A., Wang, K., Huang, L. Y., et al. (2016). Remote sensing of impervious surface growth: A framework for quantifying urban expansion and re-densification mechanisms. *International Journal of Applied Earth Observation and Geoinformation*, *46*, 94–112. https://doi.org/10.1016/j.jag.2015.11.007

Tian, W., Liao, Z., Zhang, Z., Wu, H., & Xin, K. (2022). Flooding and overflow mitigation using deep reinforcement leaning based on Koopman operator of urban drainage systems. *Water Resources Research*, *58*(7). https://doi.org/10.1029/2021WR030939

Urich, C., & Rauch, W. (2014). Exploring critical pathways for urban water management to identify robust strategies under deep uncertainties. *Water Research*, *66*, 374–389. https://doi.org/10.1016/j.watres.2014.08.020

van Daal-Rombouts, P., Sun, S., Langeveld, J., Bertrand-Krajewski, J. L., & Clemens, F. (2017). Design and performance evaluation of a simplified dynamic model for combined sewer overflows in pumped sewer systems. *Journal of Hydrology*, *538*, 609–624. https://doi.org/10.1016/j.jhydrol.2016.04.056

van der Werf, J. A., Kapelan, Z., & Langeveld, J. (2021). Quantifying the true potential of real-time control of urban drainage systems. *Urban Water Journal*, *18*(10), 873–884. https://doi.org/10.1080/1573062X.2021.1943460

van der Werf, J. A., Kapelan, Z., & Langeveld, J. (2022). Towards the long-term implementation of real-time control of urban drainage systems: A review of performance and influencing factors. *Water Science and Technology*, *85*(2), 1295–1320. https://doi.org/10.2166/wst.2022.038

van der Werf, J. A., Kapelan, Z., & Langeveld, J. (2023). Real-time control of combined sewer systems: Risks associated with uncertainties. *Journal of Hydrology*, *617*(A), 128900. https://doi.org/10.1016/j.jhydrol.2022.128900

Van Daal, P., Gruber, G., Langeveld, J., Muschalla, D., & Clemens, F. (2017). Performance evaluation of real-time control in urban wastewater systems in practice: Review and perspective. *Environmental Modelling & Software*, *95*, 90–101. https://doi.org/10.1016/j.envsoft.2017.06.015

Vasiliev, I., Luca, L., Barbu, M., Vilanova, R., & Caraman, S. (2022). Optimal control strategy of a sewer network. *Water*, *14*(7), 1062. https://doi.org/10.3390/w14071062

Vermuyten, E., Meert, P., Wolfs, V., & Willems, P. (2018). Model uncertainty reduction for real-time flood control by means of a flexible data assimilation approach and reduced conceptual models. *Journal of Hydrology*, *564*, 490–500. https://doi.org/10.1016/j.jhydrol.2018.07.033

Vezzaro, L. (2021). Extrapolating performance indicators for annual overflow volume reduction of system-wide real time control strategies. *Urban Water Journal*, *19*(1), 15–21. https://doi.org/10.1080/1573062X.2021.1948078

Vollaers, V., Nieuwenhuis, E., van de Ven, F., & Langeveld, J. (2021). Root causes of failures in sustainable urban drainage systems (SUDS): An exploratory study in 11 municipalities in The Netherlands. *Blue-Green Systems*, *3*(1), 31–48. https://doi.org/10.2166/bgs.2021.002

Zimmer, A., Schmidt, A., Ostfeld, A., & Minsker, B. (2015). Evolutionary algorithm enhancement for model predictive control and real-time decision support. *Environmental Modelling & Software*, *69*, 330–341. https://doi.org/10.1016/j.envsoft.2015.03.005