HAPPy to Control
A Heuristic And Predictive Policy to Control Large Urban Drainage Systems

van der Werf, J. A.; Kapelan, Z.; Langeveld, J. G.

DOI
10.1029/2022WR033854

Publication date
2023

Document Version
Final published version

Published in
Water Resources Research

Citation (APA)
van der Werf, J. A., Kapelan, Z., & Langeveld, J. G. (2023). HAPPy to Control: A Heuristic And Predictive Policy to Control Large Urban Drainage Systems. *Water Resources Research*, *59*(8), Article e2022WR033854. https://doi.org/10.1029/2022WR033854

Water Resources Research

RESEARCH ARTICLE
10.1029/2022WR033854

Key Points:

- The relative impact of actuators on the performance of real-time control strategies changes during and in-between events
- Dynamically selecting actuators for optimization can ensure near-global optimal control for urban drainage systems
- Using random forest algorithms, the most influential actuators can be selected in real-time

Supporting Information:

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

Correspondence to:

J. A. van der Werf,
j.a.vanderwerf@tudelft.nl

Citation:

van der Werf, J. A., Kapelan, Z., & Langeveld, J. G. (2023). HAPPy to control: A heuristic And predictive policy to control large urban drainage systems. *Water Resources Research*, *59*, e2022WR033854. https://doi.org/10.1029/2022WR033854

Received 10 OCT 2022
Accepted 8 JUL 2023

Author Contributions:

Conceptualization: J. A. van der Werf
Data curation: J. G. Langeveld
Formal analysis: J. A. van der Werf
Funding acquisition: J. G. Langeveld
Methodology: J. A. van der Werf, Z. Kapelan, J. G. Langeveld
Supervision: Z. Kapelan
Writing – original draft: J. A. van der Werf
Writing – review & editing: J. A. van der Werf, Z. Kapelan, J. G. Langeveld

HAPPy to Control: A Heuristic And Predictive Policy to Control Large Urban Drainage Systems

J. A. van der Werf[1], Z. Kapelan[1], and J. G. Langeveld[1,2]

[1]Section Sanitary Engineering, Department of Watermanagement, Faculty of Civil Engineering, Delft University of Technology, Delft, the Netherlands, [2]Partners4UrbanWater, Nijmegen, the Netherlands

Abstract Model Predictive Control (MPC) of Urban Drainage Systems (UDS) has been established as a cost-effective method to reduce pollution. However, the operation of large UDS (containing over 20 actuators) can only be optimized by oversimplifying the UDS dynamics, potentially leading to a decrease in performance and reduction in users' trust, thus inhibiting widespread implementation of MPC procedures. A Heuristic And Predictive Policy (HAPPy) was set up, relying on the dynamic selection of the actuators with the highest impact on the UDS functioning and optimizing those in real-time. The remaining actuators follow a pre-set heuristic procedure. The HAPPy procedure was applied to two separate UDS in Rotterdam with the control objective being the minimization of overflow volume in each of the two cases. Results obtained show that the level of impact of the actuators on the UDS functioning changes during an event and can be predicted using a Random Forest algorithm. These predictions can be used to provide near-global optimal actuator settings resulting in the performance of the HAPPy procedure that is comparable to a full-MPC control and outperforming heuristic control procedures. The number of actuators selected to obtain near-global optimal settings depends on the UDS and rainfall characteristics showing an asymptotic real-time control (RTC) performance as the number of actuators increases. The HAPPy procedure showed different RTC dynamics for medium and large rainfall events, with the former showing a higher level of controllability than the latter. For medium events, a relatively small number of actuators suffices to achieve the potential performance improvement.

1. Introduction

Urban drainage systems (UDS) are designed to convey wastewater and urban runoff away from populated areas. During rainfall events, those UDS can become overloaded and lead to transient pollution through combined sewer overflows (CSOs) or stormwater outfalls. CSOs specifically can introduce a variety of pollutants into the receiving surface water bodies, with potential degradation of those (natural) waters as a consequence (Owolabi et al., 2022). Increasingly, micro-pollutant pathways through overflows and outfalls are identified within the urban water cycle (Mintenig et al., 2017; Rieckermann et al., 2011), highlighting an additional need to reduce rainfall-induced pollution loads.

The reduction of CSO pollution can be realized through the construction of additional in-line storage (Liang et al., 2021), sustainable UDS (Fletcher et al., 2014; Joshi et al., 2021), or a combination of the two (Alves et al., 2016). Spatial constraints and related investment costs, however, can inhibit such measures. Optimal utilization of the existing infrastructure, through the means of real-time control (RTC), is therefore a strategy worth exploring before large investments are made to the physical infrastructure (Pleau et al., 2005). RTC strategies use sensors and forecasts to control actuators (i.e., pumps, valves, and moveable weirs) aiming to reduce urban flooding (Mounce et al., 2020), CSOs (Dirckx et al., 2011; Jorgensen et al., 1995), pollution loading (Bachmann-Machnik et al., 2021; Weinreich et al., 1997) or environmental impact (Langeveld et al., 2013).

To achieve the aforementioned objectives, two control procedures can be distinguished: (a) Heuristic and (b) Real-time Optimization (García et al., 2015). The former uses pre-defined rules to determine the settings of the system actuators, such as pumps and valves, whereas the latter computes the best possible settings in real time through, for example, Model Predictive Control (MPC). These real-time optimization procedures have been shown to outperform heuristic control procedures by better realizing the RTC performance potential (Lund et al., 2018; Van der Werf et al., 2022). The performance potential of RTC refers to the theoretical ability of the UDS operational improvement with respect to a pre-defined objective function (often the reduction of CSO volume) through the optimal control of actuators. However, for UDS with a relatively low RTC potential, the additional investments needed compared to heuristic procedures might not outweigh the benefits (Mollerup et al., 2016). Real-time optimization can be implemented in a centralized or decentralized way. In centralized control systems, all the available data is sent to one central decision-maker, where the optimal set points for all actuators are calculated and sent back to the actuators. Given that the central decision-maker has all the information about the state of the UDS, the decisions it can make are likely to be as optimal as possible, but the complexity of the optimization problem is also relatively high. On the other hand, in distributed or decentralized control methods, the calculation of set-points is done semi-locally, with limited knowledge of the state of the full system (Giordano et al., 2014). This reduces the complexity of the optimization problem, but the costs and real performance associated with the set-pints determined this way are still unknown (Garofalo et al., 2017) and may not yet reach the full potential of centralized MPC strategies as it cannot consider potentially key interactions (Kändler et al., 2022).

The performance potential of RTC depends on various UDS characteristics. Larger UDS are more likely to have an increased performance potential compared to smaller ones (Quaranta et al., 2022; Schütze et al., 2008; Van der Werf et al., 2022). However, large catchments also suffer from higher computational costs as larger models are necessary to adequately describe the UDS dynamics. Furthermore, an increased number of actuators to optimize results in a larger search space, which increases the computational time further. To enable centralized MPC for larger UDS, (partial) linearization or oversimplification of the UDS dynamics are often used but can introduce significant uncertainties into the internal-MPC model, which can result in the loss of control performance potential (Van der Werf et al., 2023) or requires application of increasingly complex algorithms (e.g., Oh & Bartos, 2023; Svensen et al., 2021). As Naughton et al. (2021) point out, the lack of clarity on the performance potential of real time optimization as well as the complexity of the procedures and algorithms and mistrust for oversimplified models are clear barriers for the widespread implementation of MPC strategies. Using embedded non-linear internal-MPC models, which provide more interpretable handles for the optimization, makes MPC practically unachievable for larger UDS due to the *curse of dimensionality* (Sadler et al., 2019). Simplifying the control procedures, whilst retaining the performance potential of real-time optimization is therefore a potential route to ensure the implementation of MPC strategies.

Global Sensitivity Analyses (GSA) have previously been used to identify actuators with the highest level of impact on the UDS performance, for optimization within a control strategy for larger catchments with many actuators (Langeveld et al., 2013; Saagi et al., 2018). However, the results of a GSA might differ depending on uncertain parameters in the model (Ledergerber et al., 2020). Given this dependency on model parameters, changes in the sensitivity of the performance of the RTC procedure to each actuator might change during and in between events. Real-time optimization could then potentially be applied to only the most relevant actuators, limiting potential risks of unforeseen dynamics introduced through a new control procedure to a sub-section of the UDS.

This paper aims to assess if the dynamics of the relative importance of actuators within a RTC procedure changes and can be predicted. It further aims to utilize this to combine heuristic and optimization-based control. It proposes a methodology to enable near-global real-time optimization of the operation of large and complex, non-linear UDS by reducing actuator dependency and aims to understand key dynamics emerging from the operation of combined heuristic and real-time optimization control.

2. Methodology

To circumvent the inhibitive computational cost due to too many actuators or reduce the potential impact of uncertainties on the performance of RTC, a Heuristic And Predictive Policy (HAPPy) is proposed. The policy design framework is modular and consists of three stages: (a) the preparative steps, (b) the HAPPy procedure (which is the implementable control procedure) and (c) the evaluation stage (Figure 1a). The various preparative steps are detailed in Section 2.1. The real-time optimization procedure, hereafter the HAPPy procedure, follows an adjusted version of the MPC algorithm proposed by Sadler et al. (2019) (Figure 1b). The changes compared to the established MPC procedure structure are highlighted by dashed blue lines and further detailed in Section 2.2. All UDS modeling in this work was done using the SWMM5 (version 5.1.015, Rossman, 2015) software and using the python programming language interface PySWMM (McDonnell et al., 2020).

2.1. Preparative Steps

The following section, highlighted in Figure 1a, sets out the preparative steps within the HAPPy, to be done prior to the implementation of the real-time optimization part. The preparative steps are, similar to the entire policy design framework, modular, meaning that any of the respective parts within these steps can be updated or

10.1029/2022WR033854

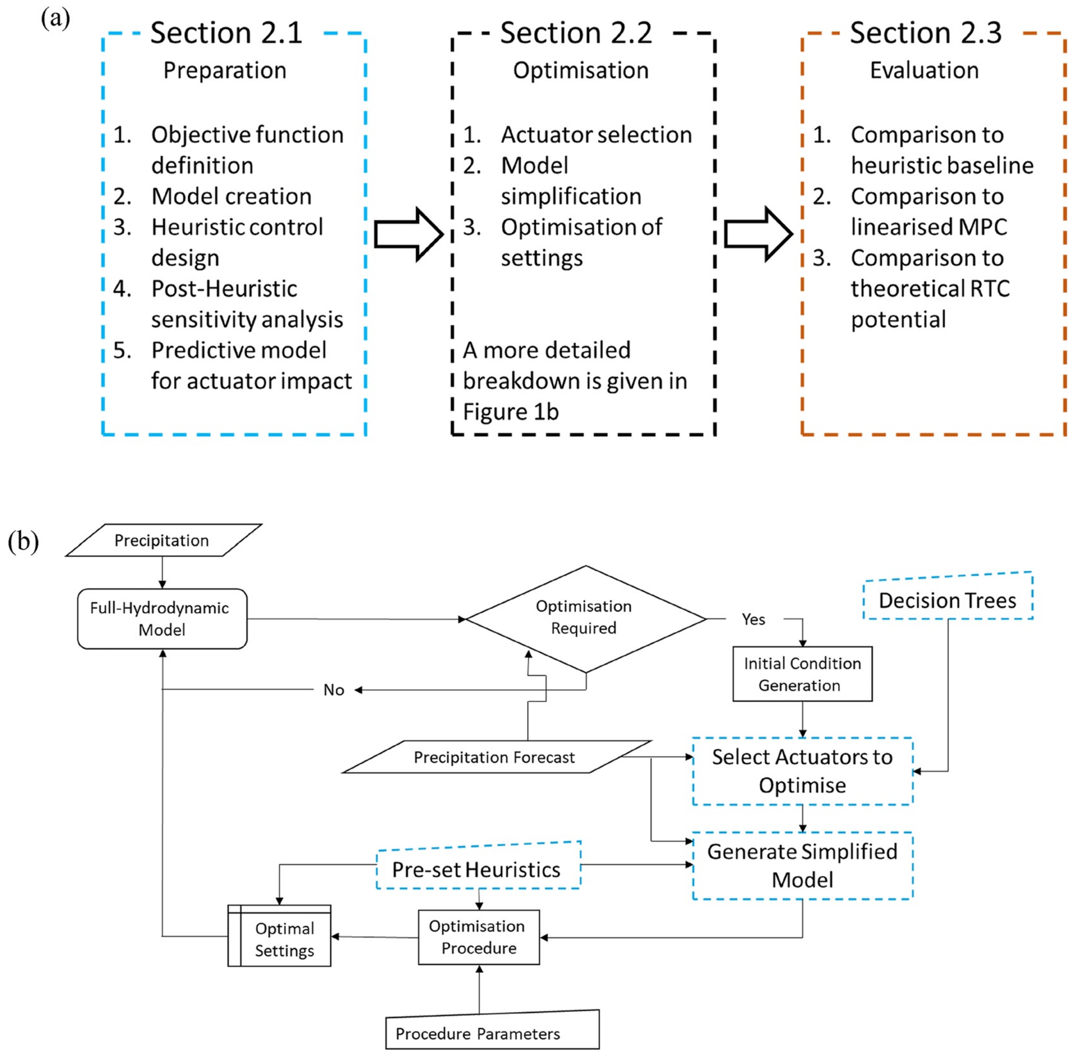


Figure 1. (a) Overview of the steps of the HAPPy, following the outline of this paper. The offline section is highlighted by the dashed blue lines, the HAPPy procedure in black and the posterior analysis in red. This is followed by (b) the layout of the real-time optimization part of the HAPPy: the HAPPy procedure. The various blocks, including the optimization required, depend on operator preferences and will be discussed in more detail in Section 2.2.

changed without directly affecting the applicability of the other parts of the policy. Improvements or adjustments can therefore be made based on new algorithms or dependent on UDS-related preferences.

2.1.1. Objective Function, Model Development and Heuristic Control

The first three steps in the HAPPy follow the steps previously proposed to design offline, heuristic control strategies (Schütze et al., 2008). First, an objective function has to be set up. The HAPPy can take any objective function related to control strategies including CSO volume minimization, weighted CSO volume minimization (when the impact of different CSOs is different), CSO pollution load minimization, environmental impact minimization, energy consumption or a combination). Here, a weighted volume-based minimization function is defined, following the definition used by Vezzaro and Grum (2014):

$$\min\left(\sum_{i=1}^{N_a} w_i * \sum_{t=0}^{T_H} Q_{i,t}\right) \tag{1}$$

where N_a is the number of actuators, w_i is the dimensionless weight associated with the ith CSO structure, T_H is the time horizon used in the analysis [s] and $Q_{i,t}$ is the overflow rate for the ith CSO structure at time t [m^3s^{-1}].

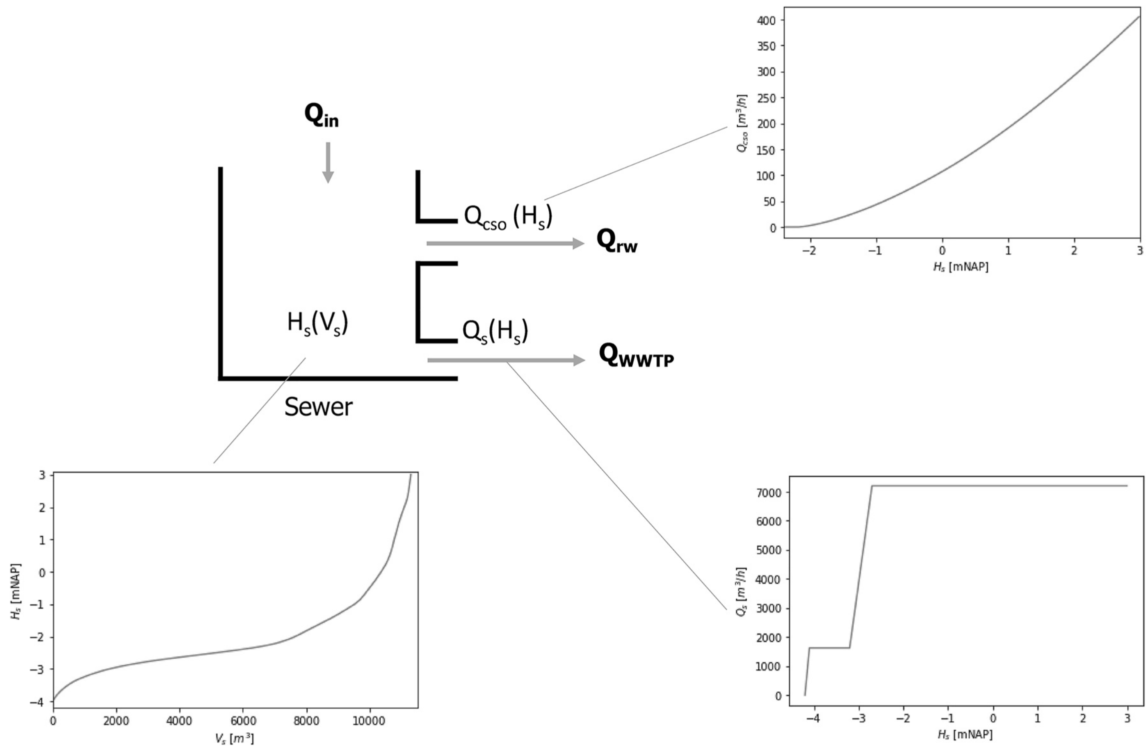


Figure 2. Schematization of the dynamic virtual reservoir model used. Q_s either goes to the wastewater treatment plant (WWTP) (as per the example here), but can also connect to a downstream reservoir. All the inflows into the reservoir (wastewater and urban runoff) are represented by Q_{in}. Q_{rw} is the final CSO overflow rate, H_s the stored volume (V_s) derived head in the reservoir. Visualization is adapted from van Daal-Rombouts et al. (2016).

After the objective function is defined, a fit-for-purpose model has to be selected and calibrated. For the use in the HAPPy, the model, functioning as the internal MPC model, has to (a) retain the key topological structure (determined by the layout of the actuators) of the UDS, (b) have a low computational cost, (c) describe the desired UDS dynamics, (d) use available real-time data to generate all initial conditions and (e) include real-time rainfall forecasts as a forcing input. A set of virtual dynamic reservoirs linked through actuators is used here to represent the analyzed sewer system. Each virtual reservoir is modeled by defining the head-volume curves for the static and dynamic storages of the part of the sewer system that it represents. The dynamic virtual reservoir model set out by van Daal-Rombouts et al. (2016) is used for that purpose. The virtual reservoirs are linked through designated links representing pumps, orifices or other actuators. Virtual reservoir's outflow Q_s (see Figure 2) links therefore either to a downstream virtual reservoir's inflow Q_{in} or to a final sewer system outflow. As the actuators are the only links considered in the model (the rest of the conduits are simplified using the dynamic reservoir model), a topological graph is created this way. The chosen model structure needs to be calibrated to ensure the validity of simplified model outputs.

Using the selected model, the heuristic control procedure forming the foundation of the HAPPy is developed. Similar to the model structure, the nature of the heuristic control procedure depends on the operators' preferences. Methodological approaches to aid in the rule-making processes (Kroll et al., 2018; Mollerup et al., 2016) and formal optimization procedures (e.g., Van der Werf et al., 2021) can be followed to generate the set of heuristic procedures. Although all forms of heuristic control can be used, the preference here is given to rule-based control (RBC), with pre-defined thresholds used to determine the set points of the actuators in the UDS. RBC was chosen as the heuristic strategy as it is commonly used in practice and allows for more interpretable results and a better ability to understand the interactions between the HAPPy procedure and the pre-made heuristic control.

2.1.2. Global Sensitivity Analysis

To quantify the level of impact of the actuators on the UDS operation performance, a global sensitivity analysis can be used (Langeveld et al., 2013; Ledergerber et al., 2020). Using the heuristic control policy, a set of rainfall events $\{P\}$ is simulated, with the system state $\mathbf{y_t}$ saved as initial conditions and ϵ_t as the forecasted rainfall at time step t. Here, a perfect forecast was used to assess the maximum theoretical performance of the HAPPy approach without practical uncertainties included. This is done for every control time step t during the simulation, creating a paired set of initial conditions and forecasted rainfall for each event. For each paired set, a GSA is performed, simulating the UDS over the time horizon of the forecasted rainfall. A forecasting horizon of 1 hr was chosen, balancing the computational cost associated with GSA and the available real-time forecast used in RTC (2 hr forecasts being available in real-time, updated every 5 min). Fifteen rainfall events were used to generate the data set used in the GSA. The start of a rainfall event was defined as the first moment rainfall falls in the catchment until the moment the UDS has returned to dry weather flow conditions.

The GSA uses a Monte Carlo type approach, sampling actuator settings using a Latin Hypercube technique, drawing values $\{k \in \mathbb{R}^n | \, 0 \leq k \leq 1\}$ for n number of actuators, where 0 means a complete restriction of flow through the actuator (or the "*off*" setting for a pump) and 1 is fully open (or the "*fully on*" setting for a pump) and any value between partial opening or activation of the pumping station (subject to pumping station specifics). Each Monte Carlo simulation constitutes 1,500 model runs (in previous work, Benedetti et al. (2012) found 1,200 runs for the GSA in the wastewater modeling context sufficient).

For each run in each Monte Carlo simulation, the objective function value is calculated, with the final value for each run being estimated as the difference between the objective function value obtained for the run and the corresponding value obtained using the heuristic control procedure (as set up in the previous section). A multi-linear regression between the actuator settings and the above difference in RTC performance is performed, generating a set of coefficients $\boldsymbol{C}_i = \{c_{\text{mlr}} \in \mathbb{R}^n\}$ where c_{mlr} are the multi-linear regression coefficients and n is the number of actuators in the system for the ith unique combined set of initial conditions and forecasted rainfall. The computed coefficients are used as an indicator of the impactfulness (ability to influence the final objective function) of each actuator (note that all random samples are in the range [0, 1]). A ranking, R, based on the computed coefficient per actuator, is made per paired set of initial conditions and forecasted rainfall, following $R_i = \text{rank}(|C_i|)$.

2.1.3. Random Forest of Decision Trees

To predict which actuators should be included in the optimization procedure, the set of initial conditions, rainfall forecast and impactfulness ranking results (based on the GSA results) are used to generate Decision Trees (DTs). In this process, let $\{N \in \mathbb{Z} | \, 0 \leq N \leq A_n\}$ where A_n is the number of actuators in the system and N the number of actuators to be included in the optimization procedure. N is a pre-determined variable, to be set by the operator, based on an experimental understanding of the functioning of the HAPPy approach. The influence of the number of actuators included is explicitly investigated by changing the value of N and assessing the relevant RTC performances. A limit of 8 actuators was chosen as a threshold to balance the range of options investigated whilst retaining the computational improvement through the use of the HAPPy procedure. The ranking results for each combined set of initial conditions and forecasted rainfall are then transformed into a binary data set through:

$$\text{BO}_{n,i} = \begin{cases} 0 & \text{if } \boldsymbol{R}_{i,n} > N \\ 1 & \text{if } \boldsymbol{R}_{i,n} \leq N \end{cases} \tag{2}$$

where $\text{BO}_{n,i}$ is a binary value indicating inclusion (1) or exclusion (0) for the nth actuator in the system at the ith combined set of initial conditions and forecasted rainfall given its rank $R_{i,n}$. These binary values are combined into binary inclusion sets, BIS, per combined set of initial conditions and forecasted rainfall such that for all n actuators: $\text{BISi} = \{\text{BO}_{n,i}\}$.

The data, consisting out of 261 unique initial condition and forecasted rainfall pairs and the binary inclusion sets, is then split (randomly) in a training and validation data set, with a 75/25 ratio respectively. The training set is used to generate a DT and the validation set is used to test and ensure the transferability of the DT results to unseen data, with a DT generated for each actuator. Rather than using one DT, an ensemble of DT forming a Random Forest model was used. Random forest models have previously been shown to have the potential to accurately predict complex UDS dynamics (Montes et al., 2021). The random forest model consists of 100 individually trained DTs per actuator based on a randomly sampled subset of 50% of the training data to ensure the DTs are trained on different sets of data. Each DT within the random forest votes on the inclusion of the Nth actuator and the actuators with the most votes are selected for optimization.

Due to the potentially skewed nature of the data set decisions (a relatively small portion of actuators is selected), an F1-score (the harmonic mean of the precision (ratio of correctly predicted positive values and total number of predicted positive values) and recall scores (ratio between all correctly predictive positive values and the number of positive values in the data set)) is used to determine the predictive prowess of the random forest of the DTs:

$$\mathrm{F1} = \frac{2 * \mathrm{Precision} * \mathrm{Recall}}{(\mathrm{Precision} + \mathrm{Recall})} \tag{3}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{4}$$

$$\mathrm{Recall} = \frac{TP}{TP + FN} \tag{5}$$

where TP is the number of true positives, FP is the number of false positives and FN is the number of false negatives. The F1-score is a value bound between 0 and 1, with 0 indicating the worst possible performance and 1 a perfect prediction.

2.2. Real-Time Procedure

When the offline section of the HAPPy is done, the real-time optimization part can be implemented. The following section expands on the HAPPy procedure. Here, the steps which are taken at every sampling interval (time step for optimization) in the optimization procedure, highlighted in Figure 1b, are expanded on. The procedure relies on the heuristic rules being applied to all the actuators, except for those selected using the random forest method, which are optimized in real-time following the procedure below. This procedure is run only when the objective function can be affected by the operation of the actuators (the optimization Required decision shown in Figure 1b).

2.2.1. Model Simplification

To decrease the computational time of the internal-MPC model, an algorithm to further simplify the internal-MPC model, based on the selected actuators, at every time step is set up. To simplify the model, the schematized topology of the UDS, forming the basis of the internal MPC model as expanded in Section 2.1, is considered as a graph $G = (V, E)$ where V are the virtual reservoirs and E are the actuators within the UDS. The virtual reservoirs encompass the storage of all the conduits and manholes within the UDS, except the optimizable actuators. Based on the random forest model output, a subset of optimizable actuators $A \subseteq E$ is defined, where A has the size of the number of actuators selected by the DT (N). The internal model is then run following the heuristic procedure, with the lateral inflow time series per V defined as Infv.

A subset of the set of virtual reservoirs $V^* \subseteq V$ is defined such that all the reservoirs affected by the settings of the actuators A are included. For each of the virtual reservoirs in V^*, every possible path to the most downstream node (usually the wastewater treatment plant (WWTP) is generated. For each path, the actuators included in the path are added to the set A and similarly, the virtual reservoirs are added to the set V^*. Lastly, any actuators which are not in the subset A, but are dependent on the state (water level) of any of the virtual reservoirs in subset V^*, through the heuristic control procedure, are added to the subset A. This procedure is run iteratively until all relevant actuators are included in the simplified internal MPC model.

An example of the simplification of the model following this procedure, done at every time step, is graphically shown in Figure 3. This simplified internal MPC model can be run using the Infv and rainfall predictions as inflow to linear reservoirs in subset V^*. This simplified internal MPC model is used to optimize the selected actuators, whilst the other actuators follow the predefined heuristic rules.

2.2.2. Optimization

The previously generated simplified internal MPC model is used to optimize the actuator settings following established MPC procedures (e.g., Sadler et al., 2019). Any optimization algorithm can be used for the optimization process, but as the framework developed here is meant for both uncertainty reduction through information dependency reduction and the potential application of real-time optimization of non-linearized UDS, a derivative-free optimization method had to be selected. Because of this, it was decided to optimize the operation

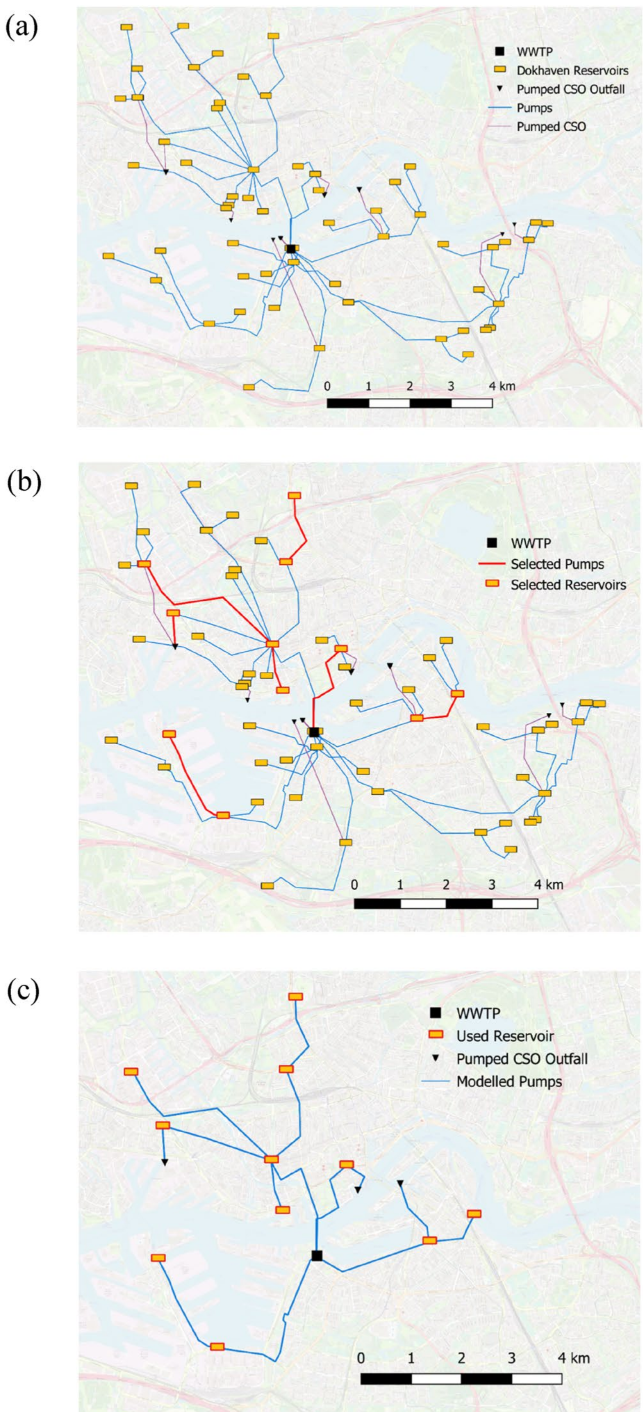


Figure 3. Here, the three stages of the model complexity reduction are shown. (a) Shows the full model of virtual reservoirs connected through pumps, followed by (b) the pumps (actuators) selected for optimization in red and (c) the topology of the final model. The final topology includes all selected pumps, as well as the pumps which can be influenced by the settings of the optimized pumps (i.e., when the setting of an actuator impacts the downstream district, which is part of the heuristic control of another pump, that last pump is included in the final model topology). Note that all the pumps are directed toward the WWTP (either directly or via downstream districts) or the pumped CSO outfalls (black triangles).

using the elitist genetic algorithm (GA). GA is a well-established optimization algorithm in the urban water literature (Rauch & Harremoes, 1999) and remains a popular optimization algorithm in recent RTC publications (e.g., Abou Rjeily et al., 2018; Rathnayake & Anwar, 2019). It also has the potential to be parallelized, enabling a more efficient search for optimal solutions (Sadler et al., 2019). GAs can be applied to highly non-linear RTC problems (including impact-based RTC), making the application more generic. Other derivative-free optimization algorithms with similar characteristics could be selected (particle swarm optimization and simulated annealing) but their implementation has been less ubiquitous in the RTC literature and are unlikely to perform better compared to a GA. The hyper-parameters used for the GA optimization are dependent on the simplified internal MPC model and the number of actuators selected through the HAPPy algorithm. Hyper-parameter optimization is therefore recommended to be performed separately for each RTC problem. In this work, a population size of 50, a parent portion of 0.16 and a mutation probability of 0.1 were used. There is no maximum number of iterations, but a time limit equal to the sampling interval was used. If prior to exceeding the sampling interval no improvement is found for 15 generations, the GA terminates, at which point convergence to the optimal is assumed (see Section S4 in Supporting Information S1 for the details of the used parameters in the procedure and preparative work).

2.3. Performance Evaluations

To ensure the relative improvement of the HAPPy over the basic heuristic control procedure, a model-driven performance evaluation following the steps set out by van Daal et al. (2017) was followed. Previously developed absolute relative performance indicators (aRPI, van der Werf et al., 2021) and the relative CSO volume (the ratio between the CSO volume using the RTC procedure and the statically optimized performance of the UDS) were used to assess the functioning of the control procedure. The aRPI gives the ratio between the difference in RTC performance and a static baseline compared to the difference between the static baseline and the maximum potential performance. This maximum potential performance is computed based on an adjusted form of the Central Basin Approach (CBA), originally developed by Einfalt and Stölting (2002). This adjusted version explicitly considers the pumping capacities as a limiting factor in the procedure by iterating through the pumped catchments and generating a central basin per sub-catchment cascade, making it better suited for UDS which includes pumps. The minimum CSO volume is generated for each subsection in each cascade (containing N-linked sub-catchments starting from the most upstream and adding a sub-catchment per iteration). From this set of minimum CSO volumes, the largest CSO volume is selected, as this reflects a limiting dynamic within the cascade of reservoirs. This largest CSO volume represents the maximum RTC potential per cascade in the UDS. A detailed breakdown of these steps can be found in van der Werf et al. (2021). The static baseline here is the underlying optimized heuristic procedure, therefore not requiring additional settings to be generated for the computation of the aRPI.

Additionally, to compare the performance of the proposed procedure, a linearized model was created. The virtual dynamic reservoirs in the connected model are thereby replaced by simple static linear reservoirs connected through actuators, simplifying the model with respect to the dynamic storage capacity and overflow dynamics (details on the implemented model are in Section 3). Within this linear reservoir model, any inflow exceeding the

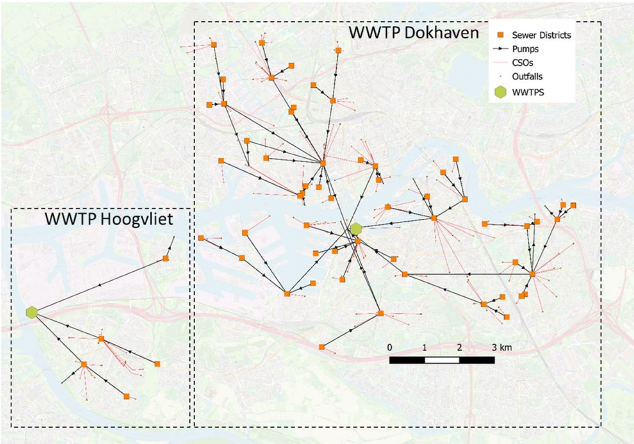


Figure 4. Spatial overview of the two UDSs used here.

available static capacity of the reservoir is assumed to be discharged through a CSO structure. The flow capacity of the actuators in the UDS is used as either continuous variables (for moveable gates or frequency-controlled pumps) or integers (in the case of binary decision variables). The performance of the HAPPy procedure is then compared to the performance of linearized optimized MPC, using the linearized model as an internal-MPC model, the COIN-OR solver (originally developed by Lougee-Heimer (2003)) as an optimization algorithm and the original model of connected virtual dynamic reservoirs as the representative model of the UDS. The details of the linearized models used here can be found in the following section.

A comparison is also made to the real-time optimization of the settings of the N-actuators statically selected as those being the most frequently important actuators (i.e., the HAPPy procedure without the dynamic selection of the relevant actuators). This statically selects the actuators for the optimization (Statically Selected Actuators Optimization, SSAO run) procedure and was used to assess the relevance of the dynamic selection of the actuators within the proposed procedure.

3. Case Descriptions

The urban runoff and wastewater of the city of Rotterdam discharge through 3,043 km of gravity and pressure pipes to three separate WWTPs: Dokhaven (564,000 p.e.), Kralingseveer (400,000 p.e.) and Hoogvliet (112,500 p.e.). The sum of the impervious connected areas totals 3,035.6 ha, draining through combined sewer systems with an average storage capacity of around 9 mm. For brevity, WWTP Kralingseveer is omitted as the associated UDS characteristics are similar to WWTP Dokhaven. Conceptual models, following the dynamic reservoir model principle (see Section 2.1), of the two other UDS were implemented in EPA SWMM5 (version 5.1.015, Rossman, 2015). A detailed map of the UDSs is given in Figure 4.

During dry weather flow, the three WWTPs function independently from each other. During extreme wet weather flow conditions, due to rising water levels in the urban canals, the UDS can become interconnected and can therefore not be seen as separate catchments during these conditions. However, as the control strategy developed here focuses on the reduction of CSO volumes, events that can cause this interconnectedness of the UDS (i.e., extreme rainfall events with a return period above 1-in-2 years) were omitted from the rainfall data set. The two catchments are therefore considered to be strictly separate in their dynamics.

CSOs in all three sections of the UDS spill to either the city canals, with a relatively high ecological sensitivity to CSO discharges, or to the New Meuse river, characterized by large flow rates, intense shipping activity and saline intrusion. Due to the discrepancy in the sensitivity, the reduction of overflows in the city canals should be prioritized. In previous work, sensitive areas are penalized more within the objective function (Vezzaro & Grum, 2014) and the same method was used here, with a weight of 10 used for the more sensitive areas and 1 for the discharges to the New Meuse river (as was previously proposed by Geerse and Lobbrecht (2002) for this catchment). Applying this, the objective function for the real-time optimization part of the HAPPy, the static version of the HAPPy procedure which doesn't select the relevant actuators dynamically (the SSAO run) and the two full-MPC procedures, adapted from Equation 1, becomes:

$$\min\left(w_1 \sum_{i=1}^{N_{a,\mathrm{NM}}} \sum_{t=0}^{T_H} Q_{i,t}^{\mathrm{NM}} + w_2 \sum_{i=1}^{N_{a,\mathrm{CC}}} \sum_{t=0}^{T_H} Q_{i,t}^{\mathrm{CC}}\right) \tag{6}$$

where $N_{\mathrm{a,NM}}$ is the number of CSO structures discharging to the New Meuse River, w_1 is the weight associated with these discharges (here, a value of 1 is used), T_H is the horizon over which the objective function is solved (here a horizon of 2 hr was chosen), $Q_{i,t}^{\mathrm{NM}}$ is the overflow rate (in m^3/hr) of the ith CSO structure discharging into the New Meuse river at time t, $N_{a,\mathrm{CC}}$ is the number of CSO structures discharging to the sensitive city canals, w_2 is the weight associated with these discharges (here, a value of 10 is used) and $Q_{i,t}^{\mathrm{CC}}$ is the overflow rate (in m^3/hr) of the ith CSO structure discharging into the city canals at time t. Given that the objective function presented here only optimizes the UDSs with regard to CSO volumes, the optimization only runs when wet weather flow conditions are either observed or when it will occur within the objective function horizon (i.e., when rainfall will fall or when anywhere within the UDS the filling degree exceeds what can be expected from wastewater only). This, within the HAPPy procedure, is the *Optimization Required* section (see Figure 1b). The urban catchment connected to WWTP Dokhaven is characterized by 61 different sewer districts, connected through pumping stations, totaling an impervious area of 1,632 ha. The districts vary in their storage capacity from 7.45 to 14.7 mm (with a total storage of 10.13 mm). A total of 160 CSO structures discharge excess wastewater into city canals or the New Meuse river. Additionally, 8 pumped CSO were installed in the system, enabling the controlled discharge of wastewater to the New Meuse river. The WWTP Dokhaven catchment was used to assess the key dynamics of the HAPPy, including the influence of the number of actuators on the performance of the HAPPy procedure and the interplay between the optimization and the heuristic control. The HAPPy procedure applied to the WWTP Dokhaven catchment is compared to a full MPC procedure relying on a linearized version of the model and optimized using a linear programming solver (see Section 3.2 for further details on both the linearized model and the solver).

The WWTP Hoogvliet catchment is considerably smaller, with a total connected area of 286.8 ha, with five district storage capacities varying from 7.31 to 14.15 mm (with a total storage of 10.68 mm). From the five districts, three (districts 1, 2, and 3) discharge directly into the WWTP, whilst district 4 discharges into district 1 and district 5 into 2. Both districts 2 and 3 have pumped CSOs, which can discharge wastewater directly into the New Meuse river. The HAPPy algorithm is therefore not necessary, as an MPC procedure applied to all five actuators in the catchment would be possible. However, because of this, it allows for the comparison of the HAPPy algorithm and two full-scale MPC systems: using the linearized model in combination with the COIN-OR solver (expanded on further in Section 3.2) and the dynamic virtual model implemented in EPA SWMM5 combined with a GA. This allows the assessment of the proximity to optimality and potential difference in MPC methods.

Both the WWTP Hoogvliet and WWTP Dokhaven UDS were modeled using the virtual reservoir methodology highlighted in Section 2. Each district within the UDSs was modeled following this methodology. The reservoirs were implemented in the EPA SWMM5 software and linked through pumps (representing the pumping stations within the UDS) with the respective capacities and the control rules (set out in the following section) added. The layout of the WWTP Dokhaven model can be seen in Figure 3a.

3.1. Heuristic Control

The heuristic control procedure underpinning the HAPPy algorithm was developed as part of the Central Automated Control 2.0 (CAS2.0) project initiated by the municipality of Rotterdam. The control strategy is set up as a multi-objective heuristic control procedure, aiming to balance the reduction of urban flooding and total CSO volume (by activating all available in-sewer storage), emissions from the WWTPs (by limiting the flow toward the WWTPs during rainfall events) and minimize the CSO volume toward the urban canals (by prioritizing the CSOs spilling toward the Nieuwe Maas river). This is achieved through the offline optimization of set points (partial or complete activation and deactivation) of pumping stations with thresholds based on the current local filling degrees and the total flow toward the WWTPs. The offline optimization of the set points for the wet weather flow conditions as well as the relevant thresholds is driven by the same objective function as previously mentioned (Equation 6). This objective (weighted CSO reduction) is realized through the limiting pumping capacities to minimize CSO volume in sensitive areas throughout the catchment and effective use of the pumped CSO. The parameters of the heuristic *if*-then control procedure within the HAPPy procedure are relevant only during wet weather flow conditions, although part of the CAS2.0 procedure relates to the flattening of the dry weather flow loads. As the application of the procedure here focuses on the reduction of CSO loads, this part of the control procedure is not considered. Further details on the development of the heuristic control method can be found in Langeveld et al. (2022), whilst additional details are described below.

The control procedure details for the WWTP Hoogvliet UDS are set out further in Table 1. It can be seen that, to avoid overloading the treatment plant, the flows from districts 1 and 2 are reduced. The activation of the CSO pumps (PCSO 2 and 3) are both at filling degrees of 80% of the district in which the CSO pumps are situated, balancing the sufficiently early activation of the CSO pumps to reduce CSOs discharging to the urban canals whilst minimizing the pumped CSO overflow volume. The implementation of CAS2.0 for the WWTP Dokhaven takes a similar structure to that of the rules implemented for WWTP Hoogvliet and is shown in Supporting Information S1 (Table S3).

Table 1
Overview of the Heuristic Procedure Optimized for the WWTP Hoogvliet Catchment

Actuator ID	Catchment ID	Rule details
P1	District 1	If the total discharge to the WWTP > **3,300** m^3/hr, then reduce flow to **1,000 m^3/hr**
P 2	District 2	If filling degree >**80%**, reduce flow to **380 m^3/hr**
PCSO 2	District 2	If filling degree >**80%,** then **Activate pump at full capacity**
P3	District 3	If filling degree >**80%**, reduce flow to **0 m^3/hr**
PCSO 3	District 3	If filling degree >**80%**, then **Activate pump at full capacity**

Note. The values in the Rule Details column highlighted in bold were determined using an offline optimization method. Note that these rules exclude other districts which cannot be controlled, but also discharge into the WWTP Hoogvliet.

The set points of the actuators are changed at a 15 min intervals. The minimum setting duration of the pumps in the UDS is 15 min, meaning a shorter sampling interval would not be possible. This sampling interval is used as the re-run time for the real-time optimization procedures used and functions as a maximum number of iterations within the optimization algorithm.

3.2. Linearized Model and Model Predictive Control

To enable full centralized MPC for the WWTP Dokhaven case study, a linearized version of the linked dynamic reservoir model from EPA SWMM5 is developed based on the linear reservoir tank used by Sun et al. (2020). Every district in the two catchments is described as a linear reservoir, where the water volume in the tank at the kth time step is computed as:

$$V_k = V_{k-1} - \left(Q_k^{\text{out}} - Q_k^{\text{in}}\right) * \Delta T \tag{7}$$

$$Q_k^{\text{out}} = Q_k^{\text{pump}} + Q_k^{\text{CSO}} \tag{8}$$

where V_k is the volume of water in the reservoir at time step k in (m^3), Q_k^{in} is the sum of the runoff generated by the rainfall (computed using the EPA SWMM5 software), the wastewater inflow and the potential upstream reservoirs discharging into the linear reservoir at time step k (in m^3/s) and ΔT is the time step used in the simulation (in seconds). Q_k^{out} is the outflow from the reservoir comprising the pumping capacities of the downstream pumping station and (where applicable) the pumped CSO (Q_k^{pump} in m^3/s) and CSO overflow (Q_k^{CSO} in m^3/s). When the static volume of a linear reservoir is set to be exceeded (i.e., $V_{k-1} + Q_k^{\text{in}} - Q_k^{\text{pump}} > V_{\max}$), Q_k^{CSO} is set to be equal to $V_{\max} - V_{k-1} - Q_k^{\text{in}} + Q_k^{\text{pump}}$. This oversimplifies the dynamic storage but allows for rapid optimization of the pumping capacities (the decision variables in the optimization problem).

The linear reservoirs are applied to all the districts of both the WWTP Hoogvliet and WWTP Dokhaven catchments to create a linearized model. The pumping capacities are the decision variables used to solve the objective function (see Equation 6). The optimization only runs during predicted or occurring wet weather flow (i.e., from the moment rainfall is predicted within the prediction horizon) and has a sampling interval of 15 min (due to the physical constraints of the actuators). The optimization function is subject to minimum volume constraints (no negative volumes in the reservoirs), minimum pumping capacity constraints (no negative pumping capacities), and maximum volume and pumping capacity constraints (dependent on the maximum storage capacity of reservoirs and pumping capacity per pumping station). Both models use the maximum inflow to the treatment plants as a combined constraint, as is implemented in the CAS2.0 heuristic control logic (see Table 1 for the WWTP Hoogvliet case).

3.3. Rainfall Characteristics

To capture the spatial heterogeneity of the rainfall events, radar data was used. An open data set of rain-gauge adjusted radar data (merged from various C-band radars) covering the Netherlands, was available and used (see Overeem et al. (2009) for the details on the rainfall data calibration). This data set is available as a 1 km × 1 km raster with a temporal resolution of 5 min and is a merged product of a network of rain gauges and radar data from Dutch, German and Belgium radars. For the evaluation of the HAPPy procedure implemented in the Dokhaven catchment, 7 rainfall events (distinct from those used for the generation of the random forest for the actuator selection process) from 2020 were selected for the detailed analysis of the influence of the number of actuators on the performance of the HAPPy procedure. The weighted mean rainfall over the catchments ranges from 6.77 to 33 mm (mean 19.37 mm), with a total duration ranging from 3.28 to 11.86 hr (mean 7.71 hr and a maximum intensity ranging from 6.75 to 52 mm/hr (mean 18.49 mm/hr). This spread ensures to have a wide variety of CSO-inducing rainfall events (including events with a low expected CSO volume), enabling the analysis of the RTC performance for a range of conditions. For the final number of actuators (8) included in the HAPPy procedure applied to the case of the WWTP Dokhaven, additional simulations were performed to better ascertain the HAPPy procedure performance. At total of 22 events (including the 7 rainfall events previously mentioned) were ran, with a mean weighted rainfall depth of 17.5 mm, a mean duration of 6.6 hr and a mean maximum intensity of 21.9 mm/hr. The range of these values for the 22 rainfall events is the same as in the case of seven previously described events.

The events considered for the WWTP Hoogvliet catchment, on the other hand, were larger (again distinct from those used for the generation of the random forest for the actuator selection process) with mean rainfall depths ranging from 14 to 43 mm (mean 25.3 mm), total durations ranging from 5.6 to 10.8 hr (mean 8.67 hr) and maximum intensities ranging from 10.9 to 40.9 mm/hr (mean 26.4 mm/hr). These events were selected to test the performance of the HAPPy under scenarios which have a low potential for optimization through RTC. This was to test if the HAPPy would not exacerbate CSO volumes during challenging events, a key step necessary for a robust RTC system (Van der Werf et al., 2022). Two relatively small rainfall events were included to further test if the HAPPy approach was able to generate satisfactory results within the rainfall range where RTC has the highest potential (Vezzaro, 2021). More details of all the rainfall events (for both catchments) are included in Supporting Information S1 (Tables S1 and S2).

The observed radar data is also used as the forecasted rainfall used within the (simplified) internal-MPC model, in order to minimize the uncertainties and highlight the theoretical performance potential of the HAPPy. This is done for all real-time optimization procedure runs. The same rainfall-runoff is used for the prediction of lateral inflow in the internal-MPC models as the system-representative model (including the linearized MPC, where the first step is the calculation of the lateral inflows following the EPA SWMM rainfall-runoff calculation).

4. Results and Discussion

In the following section, the results from the GSAs are discussed, followed by the prediction performance of the Random Forest algorithm for both analyzed catchments. Then, the performance of the HAPPy procedure is compared to a static form of real-time optimization, a full MPC procedure based on a linear programming and a full MPC procedure using a GA for the smaller UDS to benchmark the HAPPy functioning. Then, the HAPPy procedure, using a differing number of actuators to optimize, is applied to the larger UDS and the key dynamics observed are discussed. Two events are further examined to highlight the functioning of the HAPPy procedure.

4.1. Actuator Ranking

Dynamically selecting the most influential actuators in the system assumes a priori that this changes during and for different rainfall events. The importance of each actuator was determined using the methodology described in Section 2.1, based on the 261 (based on 15 rainfall events) binary inclusion sets of multi-linear regression coefficients obtained for each UDS. The obtained frequencies of different ranks (ranks 1 to 5 for the 5 actuators in WWTP Hoogvliet UDS and ranks 1 to 51 for the 51 actuators in WWTP Dokhaven UDS) are shown here in Figure 5. In both cases, different actuators are the most relevant (i.e., rank 1) depending on the initial conditions in the UDS and the rainfall forecast. Furthermore, the set of most influential actuators changes, meaning that the dynamic selection of multiple actuators during the event can likely lead to an increased performance of the UDS. For the WWTP Dokhaven UDS case (Figure 5b), 21 of the 51 actuators were found to be never ranked within the top 10 most relevant actuators. These were predominately pumps at the upstream ends of the catchment, connected to relatively small sub-catchments, therefore causing only minor changes in the total CSO volume. These actuators were not included in the DTs generated for this reason.

4.2. Prediction of Most Impactful Actuators

The ability to correctly predict the impactfulness of the actuators is a key step to ensure the functioning of the HAPPy procedure. For the WWTP Hoogvliet UDS (with five actuators) the validation results indicate that

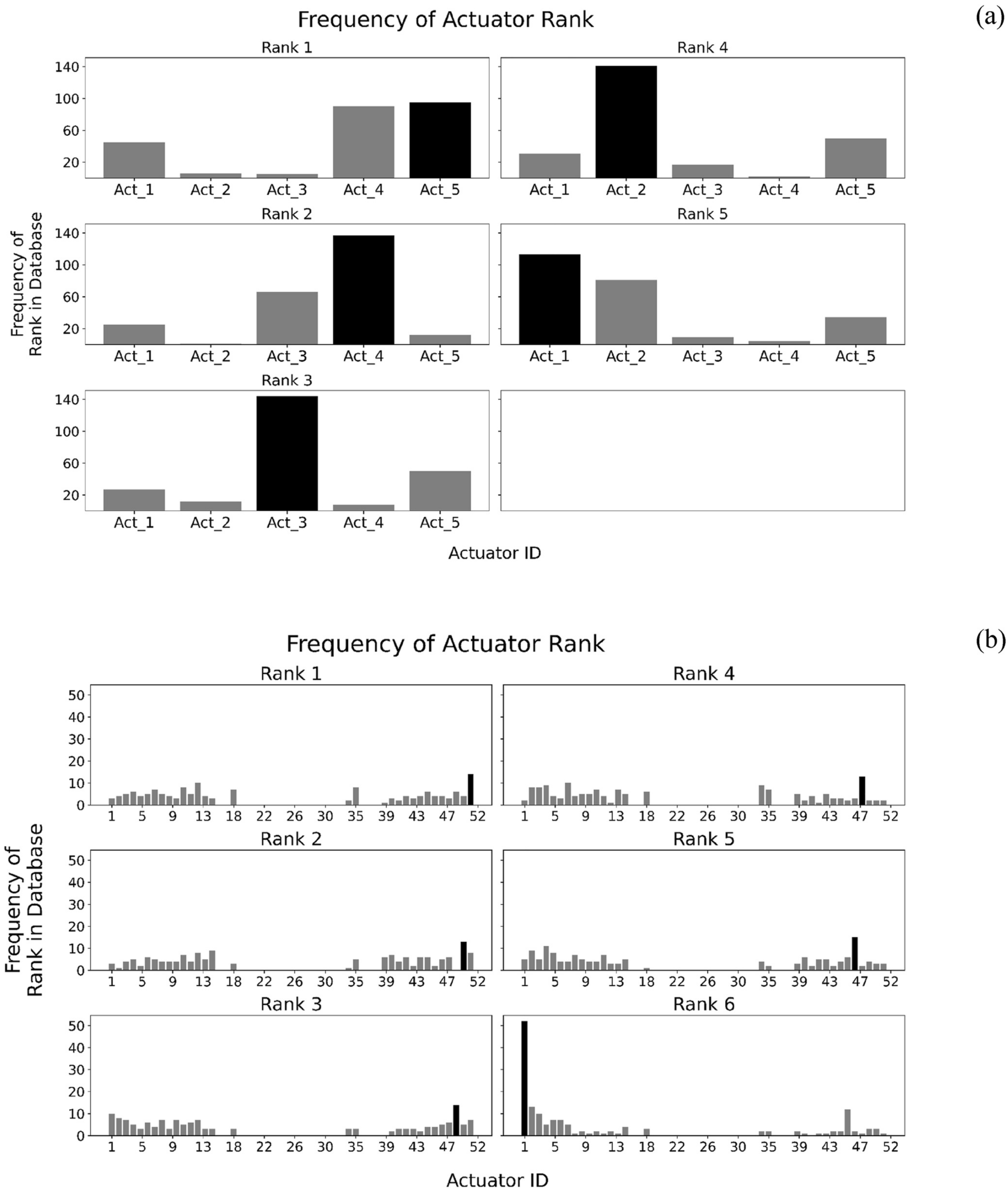


Figure 5. Overview of the frequency of the rank of each actuator for the (a) WWTP Hoogvliet catchment and (b) the WWTP Dokhaven catchment. The latter only shows the 6 foremost ranks, as these will be used in the optimization.

Table 2
Confusion Matrices of the Random Forest Results as Applied to the Validation Data Set of Both of the Catchments Studied, Predicting the 20% and 60% Most Impactful Actuators Respectively

		Catchment			
		WWTP Hoogvliet		WWTP Dokhaven	
Percentage Actuators	Predicted Actual	Positive	Negative	Positive	Negative
20%	Positive	16.3%	3.7%	14.1%	5.0%
	Negative	3.8%	76.3%	4.5%	76.4%
60%	Positive	56.9%	3.1%	54.8%	5.2%
	Negative	3.1%	36.9%	8.5%	31.4%

Note. The incorrectly predicted values are highlighted in red, and the correctly predicted ones are in green.

the random forest method is able to accurately predict 3 actuators with the highest level of impactfulness (60% of the actuators, the number used in the HAPPy procedure), given the relatively low occurrence of FN and FP (Table 2), combining to an F1-score of 0.92. When considering only the most impactful actuator (selecting 20% of the total actuators), this performance dropped to an F1-score of 0.82, correctly identifying the most impact actuator 81.7% of the time. A lower performance was observed for the WWTP Dokhaven case for the correct identification of 20% of the most impactful actuators compared to the smaller WWTP Hoogvliet case (an F1-score of 0.72 compared to 0.82, respectively). Despite the increased number of actuators and catchment size, the proposed random forest method was able to accurately predict 73% of the actuators with the highest level of impactfulness (the so-called recall value). For the 60% actuator inclusion, the F1-score increased to 0.87, again a lower score compared to the WWTP Hoogvliet case study for the same fraction of actuators predicted.

4.3. Performance Comparison—WWTP Hoogvliet

The HAPPy procedure, with three (out of 5) actuators included in the optimization, was benchmarked against a real-time optimization procedure using the three most impactful actuators (highest mean rank from the GSA) of the UDS (statically selected actuators optimization, SSAO), a full MPC procedure based on the linked dynamic reservoir models and a GA for optimization (full MPC (GA), using all actuators in the optimization procedure) and a full MPC procedure based on the linearized model using linear programming to optimize the UDS (full MPC (LP), using all actuators in the optimization procedure). The HAPPy procedure reduced the total overflow in the catchment by 5.41% for the seven events analyzed when compared to the optimized heuristic control procedure (CAS2.0) baseline (Table 3). This is relatively low compared to the previously reported RTC performance levels (Quaranta et al., 2022; Van der Werf et al., 2022) but given the rainfall depth and intensity of the events, the potential for reduction was relatively low in this case, as reflected in the maximum reduction potential through RTC (the CBA value) of 14.45%. For the two smallest rainfall events within the data set, a reduction of 18.5% relative to the optimized heuristic control (the baseline) was observed. When considering the aRPI values, the HAPPy procedure outperformed the SSAO procedure runs and differed only 0.03 aRPI points (i.e., 7%) from the full MPC performance, indicating the potential increase in performance by dynamically selecting the actuators to optimize (equating to a 33.4% increase in the reduction compared to the SSAO procedure). Comparing the two full MPC methods, the results were comparable, with no significant difference in the output, with the GA-based optimization algorithm performing slightly better. The model simplification through linearization therefore did not significantly decrease the RTC performance and the GA managed to equally optimize the operation of the UDS compared to the linear solver.

To better understand the performances of the three optimization-based RTC algorithms, the distribution of the pumped, unpumped and total CSO volumes for the seven rainfall events were analyzed (Figure 6). The HAPPy procedure performed better compared to the procedure which relies on the real-time optimization of the same three actuators (the SSAO procedure) in both the pumped and unpumped CSO volumes, with an additional total reduction of 3.3×10^3 m^3 and 1.6×10^3 m^3 respectively. Furthermore, the SSAO procedure relied on the pumped CSOs to facilitate the reduction of the unpumped CSO, as should be prioritized (according to the objective function). This led to a more than 3.0×10^3 m^3 increase in pumped CSO volume for one event. As two of the three

Table 3
Results for the Different Control Procedures

	Baseline	SSAO	HAPPy procedure	Full MPC (GA)	Full MPC (LP)	CBA
CSO Volume (in 1,000 m^3)	285.9	276.1	271.2	269.9	270.1	249.8
Reduction relative to Baseline	(−)	3.55%	5.41%	5.93%	5.84%	14.45%
aRPI	(−)	0.27	0.41	0.44	0.44	(−)

Note. The baseline refers to the heuristic control procedure developed under the CAS2.0 project.

10.1029/2022WR033854

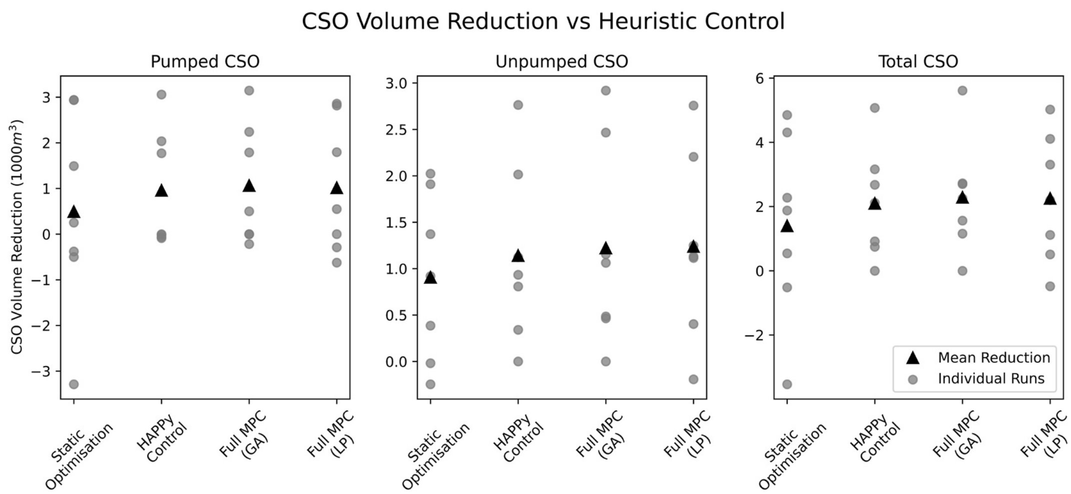


Figure 6. Comparison between three optimization forms for the Hoogvliet catchment: Statically Selected Actuator Optimization (using the global most important actuators), HAPPy algorithm (dynamically selected actuators) and Full MPC (using all actuators).

included actuators for the SSAO procedure were the CSO pumps, the controllability of the UDS through the SSAO procedure was dominated by the usage of these pumps. In the HAPPy procedure, the dynamic selection of the actuators was able to reduce the unpumped CSO rate further compared to the SSAO procedure, but without the increase in the pumped CSO rate.

When compared to the full MPC systems, the HAPPy approach performed only slightly worse, with the GA-based and linear programming-based MPC systems having an additional reduction in total CSO volume of 1.3×10^3 m^3 and 1.1×10^3 m^3 respectively (which is around 2% of the total CSO volume reduction through RTC). When assessing the relative volumes discharged through each individual CSO structure in the UDS (the overflow volume per CSO structure divided by the total CSO volume), no significant differences between the three methods were found, indicating that the resulting dynamics of the two procedures were comparable. Due to the relatively small amount of rainfall events evaluated here, statistically significant differences (using an Anderson-Darling two-sample tests) in the distributions of the overflow volume reductions, comparing the SSAO, HAPPy and the two full MPC procedures, were not found. There was no significant difference in the total CSO volume, CSO volume to the New Meuse nor the CSO volume to the city canals. An overview of the distributions for the three CSO volume types is provided in Supporting Information S1 (Figure S2).

4.4. Large Catchment Performance– WWTP Dokhaven

For the large catchment (WWTP Dokhaven), the overall performance of the HAPPy procedure with the maximum number of actuators (8) was assessed, followed by the influence of the number of actuators (ranging from 1 to 8 actuators) included in the HAPPy optimization procedure. The retrained RFs, to predict the specified number of actuators, showed only minor variations (F1-score deviation of below 0.3) for each of the included number of actuators). For each of the seven events (see Table S1 in Supporting Information S1 for the rainfall event characteristics) the performance is compared to the baseline heuristic control procedure and a fully linearized MPC procedure.

Resulting from the selection of the rainfall events, two clusters of events were observed: two events (events 1 and 5) had a large CSO reduction compared to a relatively low reduction observed for the five other events (shown as the two lowest lines in relative CSO Volume plot shown in Figure 7). As the total CSO volume in the system was dominated by the largest events (whose volumes are orders of magnitude larger than the smaller events), the total CSO volume reduction by using the HAPPy procedure was 5.2% (when 8 actuators were used), ranging from 0.9% to 100% for different events. This large range in relative reduction of CSO volume comes from the relatively large spatial spread of total rainfall depth and maximum rainfall intensity found in the analyzed events, impacting the RTC potential.

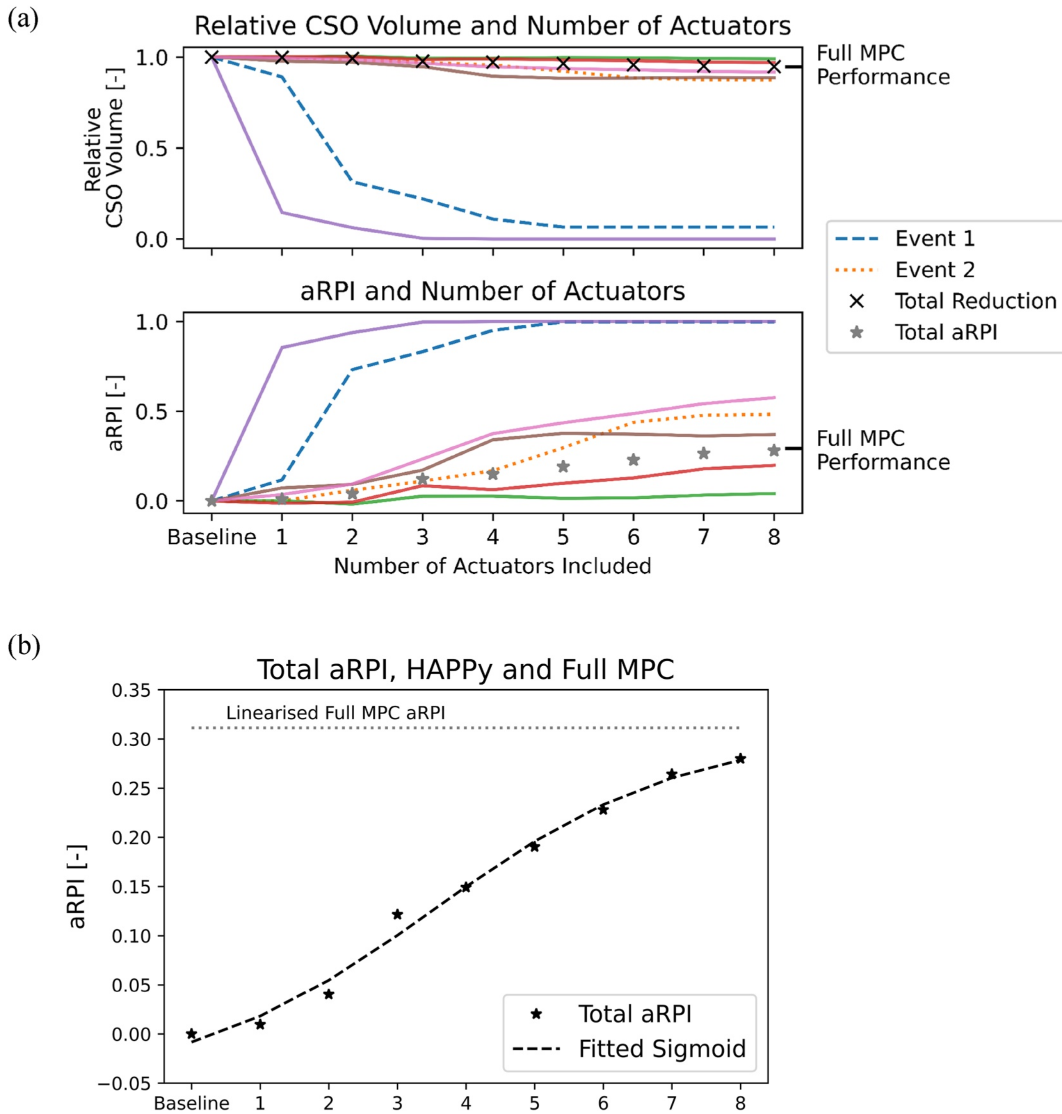


Figure 7. (a) Relation between the number of actuators included in the HAPPy procedure and performance compared to the baseline (full heuristic control) and aRPI. The dashed (blue) and dotted (orange) lines are the events further analyzed below, while the other of the events are displayed by the solid lines. (b) Shows the total aRPI dynamic with respect to the number of included actuators, showing a sigmoidal relationship. It also shows the results of the full MPC using the linearized MPC, showing the proximity of the 8 actuator HAPPy results.

A maximum total aRPI of 0.28 was obtained when 8 actuators were used in the HAPPy procedure when considering the seven events. Using the extended data set (with 22 rainfall events), the performance was slightly worse with an aRPI of 0.26, though the volume reduction increased from 5.2% to 7.1% (reducing the total CSO volume by 103.1×10^3 m^3 or 6.3 mm). A breakdown of all the results can be found in Supporting Information S1 (Tables S3 and S4). Although the influence of the number of actuators used in the optimization problem differs across events (Figure 7), a sigmoidal relation between the number of actuators and the total aRPI (using the sums of the CSO volume for the events for the baseline, HAPPy and CBA) seems to exist. A sigmoidal relation was expected as the increasing number of actuators allows for finer RTC resulting in increasing aRPI values, especially initially. A similar relation between RTC efficacy and number of actuators was found by Eulogi et al. (2020) when placing *N* number of actuators in a UDS for CSO volume reduction.

Comparing this sigmoidal relation to the performance of the fully linearized MPC procedure, a convergence of the HAPPy procedure toward the performance of the full MPC procedure can be observed (see Figure 7). However, the HAPPy procedure performance remained below the achieved performance of the full MPC procedure (with

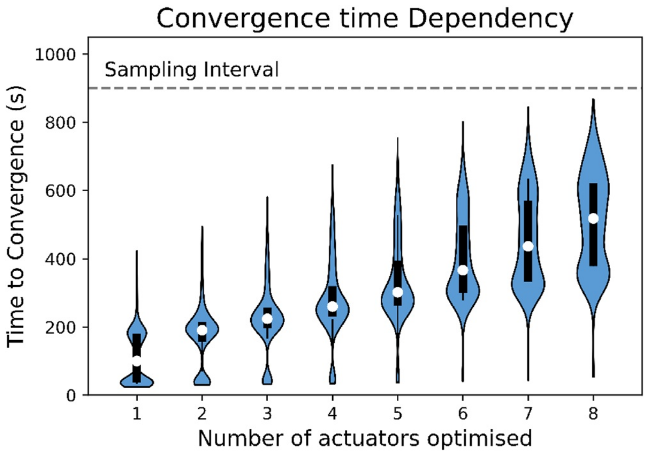


Figure 8. Overview of the distribution of the time of convergence for the different number of actuators included in the HAPPy procedure.

a total aRPI of 0.31 for the seven events combined). In the extended data set, the relative performance of the LP-MPC increased to an aRPI of 0.35, with a total CSO volume reduction of 141.7×10^3 m^3 (8.7 mm, 9.7% total CSO volume reduction). The increase in CSO volume reduction compared to the HAPPy procedure is not statistically significant (p-value of 0.063 following an Anderson-Darling 2-sample test), though the difference in aRPIs is (p-value <0.05 following the same Anderson-Darling 2-sample test). The additional uncertainties, introduced by the further linearization, therefore did not decrease the achievable potential of the MPC system for this case study. This can partially be attributed to the relatively small differences between the linearized model and the model used to represent the physical UDS (a simplified model following the linked dynamic reservoir model), as opposed to a full hydrodynamic model as per the example of Van der Werf et al. (2023). The ability, however, of the HAPPy procedure to improve the performance close to the full MPC procedure shows the potential of the procedure for UDS which cannot be linearized without excessive loss of model accuracy. Additionally, the distribution in total CSO volume reduction of the eight actuators' HAPPy procedure and the full MPC model was found to be not statistically significant (following an Anderson-Darling two-sample test), but the number of events analyzed likely accounts for this.

The investigated domain and the number of rainfall events used are too few to draw statistically significant conclusions about the underlying relation between the number of actuators and the HAPPy procedure performance. After the maximum reduction potential by using the HAPPy procedure has been achieved, further increase in actuators may negatively impacts the UDS performance: as more actuators are included, the depth of the search and potential for convergence can decrease leading to sub-optimal results in terms of the objective function. As non-impactful actuators are considered but unlikely to have an impact on the final RTC performance. However, as the convergence time (including actuator selection time, model creation and optimization) was still below the sampling interval for all runs performed across events (see Figure 8), a decreased potential of the HAPPy procedure was not observed within the used range of included actuators. Although the speed of convergence is significantly larger compared to the linear optimization problem, the algorithm can reduce the complexity to allow for non-linear models to be optimized in real-time without significant uncertainties introduced in the internal-MPC model.

Aside from the difference in (realized) RTC potential per event, two further distinct dynamics within the events could be identified in both the aRPI and relative CSO volume results: those with and without the breaking point. Here, a breakpoint is defined as a point at which increasing the number of RTC actuators by one results in an

Table 4
Change in the Total CSO Volume Reduction Compared to the Heuristic Baseline (the CAS2.0 Procedure) Per Interval of Actuators Included in the HAPPy Procedure

	Percentage change in total CSO volume reduction per actuator interval							
Event	0–1	1–2	2–3	3–4	4–5	5–6	6–7	7–8
#1	11.7	**61.6**	10.0	11.9	4.71	0.05	−0.05	0.05
#2	0	12.1	10.6	12.1	26.4	29.3	8.1	1.3
#3	0	−45.3[a]	**110.1**[a]	1.1	−32.4[a]	7.7	39.1	19.7
#4	−6.8	3.0	46.5	−11.5	18.4	14.9	25.4	10.1
#5	**85.5**	8.3	5.9	0.3	0.0	0.0	0.0	0.0
#6	19.4	5.5	21.6	45.8	9.8	−1.3	−2.7	2.0
#7	6.1	10.2	24.3	24.6	10.5	8.9	9.7	5.8

Note. The bold values indicate identified breaking points within the data set.

[a]Due to the relative loss in total CSO volume reduction at the 1–2 and 4–5 intervals, this value is above 100%. It should be noted that the increases in total CSO volume are due to an increase in pumped CSO rate, decreasing some of the unpumped CSOs.

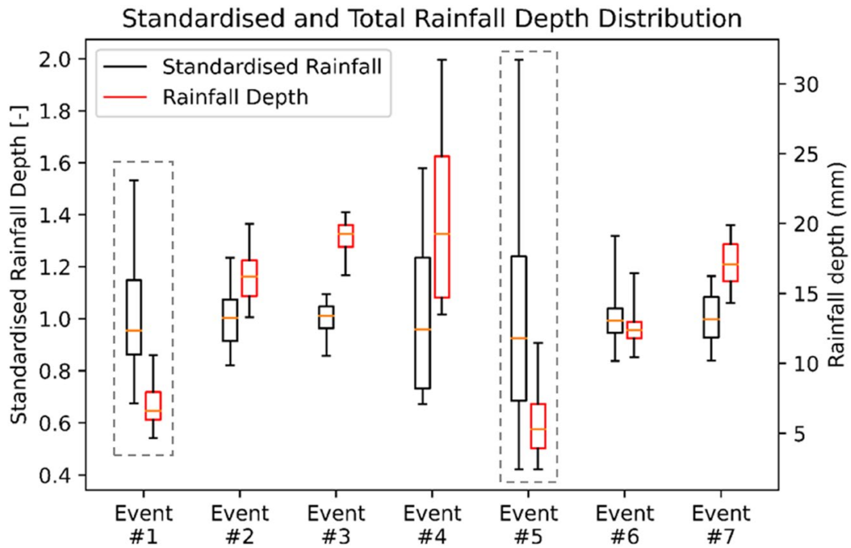


Figure 9. Standardized and total rainfall depth spatial distributions of the rainfall over the WWTP Dokhaven UDS. The distributions are based on the total depth of each pixel (a 1 × 1 km area) of the UDS urban catchment. The distributions highlighted by the dashed gray boxes are the events categorized as including a breaking point. Whiskers indicate the full range of observations during the event.

abrupt (more than 50%) reduction in the total CSO volume compared to the heuristic baseline. Following this definition, three events could be classified as having a breaking point (see bold values shown in Table 4). One of these events, Event #3, however, had an observed breaking point larger than 100% due to the relative increase in the CSO volume before the relevant interval. This increase was caused by an increase in the pumped CSO value to reduce spills toward the urban canals, as specified by the optimization objective function (see Equation 6).

The other two events (events 1 and 5) have two main characteristics in common: (a) a large spatial distribution in the standardized rainfall (standardized by dividing by the mean total rainfall depth in space) and (b) a mean total rainfall depth below the static capacity of the system (highlighted with the gray boxes in Figure 9). The former indicates the presence of a breaking point for events that have the highest potential for improvement through RTC (Vezzarro, 2021). The combination of spatial heterogeneity and relatively low total rainfall depth in the events led to CSOs occurring in only a small part of the UDS, meaning a relatively small number of correctly predicted (i.e., selected) actuators could significantly reduce the total CSO volumes. To quantify the relation between both the total depth and the spatial heterogeneity of the rainfall on the number of actuators necessary to approach optimality, additional events should be included in the analysis.

As shown above, the importance of the number of actuators included in the HAPPy procedure was found to depend on the rainfall characteristics of the event and differs between rainfall events. The current implementation of the actuator selection relies on a fixed number of actuators to be selected and might therefore not be the optimal strategy (as this maximum number is not always necessary, meaning computational costs could be further reduced).

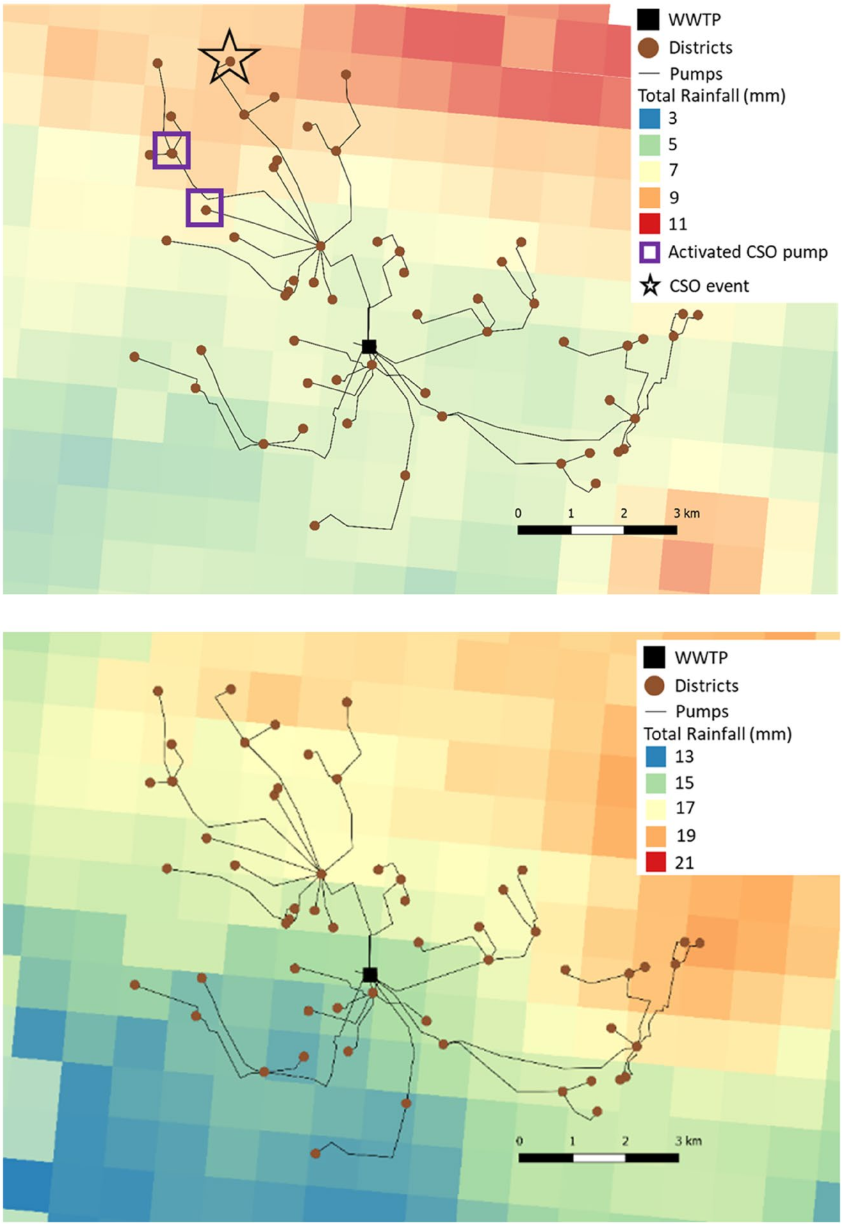
Two rainfall events (#1 and #2) were further analyzed to better understand the differing importance of the number of actuators on the performance of the HAPPy procedure and the associated dynamics, the spatial distribution of the total rainfall depths shown in Figure 10. These two are represented by the dashed and dotted lines in Figure 9 and were chosen to include an event with and without a breaking point as well as an event with high and relatively low RTC performance potential. The rainfall characteristics, UDS dynamics and interaction between the RTC performance, selected actuators, and optimization procedure are examined in further detail.

4.5. Analysis of Event 1

The first event is a highly spatially heterogeneous rainfall event, with rainfall depths exceeding the static capacity recorded only around the north-western section of the UDS (see Figure 10a), where the other parts received only between 4 and 7 mm over 36 hr (during a single peak with a mean duration of 3.3 hr). The total CSO volume of

10.1029/2022WR033854

(a)



(b)

Figure 10. Overview of the spatial distribution of the total rainfall (in mm) of the two analyzed events. (a) Shows the high spatial heterogeneity associated with Event 1, with the two activate pumped CSO locations highlighted with the purple boxes and one uncontrolled CSO event marked with a black star, and (b) the distribution of rain from the second event. Note that the rainfall depth scale is represented by the color changes between the events.

the event was caused by the activation of two pumped CSOs (located in districts 4 and 12) and one uncontrolled CSO event in district 913 (marked with the purple squares and the black star in Figure 10a, respectively). The uncontrolled CSO event could not, with the given actuator configuration, be reduced. This is reflected in the results from the CBA analysis, where the minimum amount of CSO volume discharged during the event was equal to the volume discharged through the uncontrolled CSO structure.

Given this equality between the CBA method and uncontrolled CSO discharge, the pumped CSO discharges could theoretically have been prevented. To understand the cause of the "unnecessary" discharge, the relevant heuristic rules should be examined. Within the heuristic control, the two pumped CSOs are activated at an 80% filling degree, ensuring redundancy, due to the dependency:

10.1029/2022WR033854

$$\mathrm{PCSO}_4 \bigwedge \mathrm{PCSO}_{12} \begin{cases} 1 & \mathrm{FD}_3 \geq 0.8\,|\mathrm{FD}_4 \geq 0.8|\,\mathrm{FD}_{12} \geq 0.8 \\ 0 & \text{otherwise} \end{cases} \tag{9}$$

where PCSO_n is the setting of the pumped CSO at district n and FD_n is the filling degree at district n. These CSOs are activated to alleviate the downstream area, such that when the pumped CSOs are activated, the sewer pumps are deactivated following the inverse rules:

$$P_{4\to3} \wedge P_{12\to3} \begin{cases} 0 & \mathrm{FD}_3 \geq 0.8\,|\mathrm{FD}_4 \geq 0.8|\,\mathrm{FD}_{12} \geq 0.8 \\ 1 & \text{otherwise} \end{cases} \tag{10}$$

where $P_{n\to m}$ is the setting of the pump from the upstream district n to the downstream district m. During the event, the 80% filling degree threshold was exceeded for around 45 min at district 12 (Figure S3a in Supporting Information S1), leading to the activation of the pumped CSOs.

Due to the nature of the heuristic settings, minimal CSO reduction could be achieved when 1 actuator was included (see Section S5 in Supporting Information S1 for a detailed description of the underlying mechanism). This limitation could be largely overcome by the inclusion of one additional actuator. Including 3, 4, and ≥5 actuators allowed for the reduction (3 and 4) and negation (≥5) of the pumped CSO at both districts 4 and 12 (see for detailed breakdown Figures S3–S5 in Supporting Information S1). The inclusion of 4 actuators should have been enough in the way that the HAPPy procedure was implemented, but due to the incorrect inclusion of other pumps (and therefore the exclusion of pumps related to the relevant districts), a reduction in total CSO volume was observed between 4 and 5 actuators (Figure 7a). No additional CSO volume reduction was observed for the inclusion of more actuators, but no performance drop was observed either. The linearized MPC showed similar actuator behavior to that of the HAPPy procedure when optimizing more than five actuators.

Although the synergy between the real-time optimization and the heuristic part of the HAPPy procedure managed to negate the pumped CSO event, it required the selection of 5 actuators for optimization, although the inclusion of the two CSO pumps could have sufficed. The heuristic portion of the HAPPy procedure, however, would have to be adjusted in order to allow for this. This suggests a shift in the optimality of the rules could occur when local actuators are optimized in real-time, able to more effectively synergize between real-time optimization and heuristic procedures.

4.6. Analysis of Event 2

The second event was of a considerably larger magnitude, with the total rainfall exceeding the static capacity throughout the catchment (Figure 10b). This means a combination of controlled and uncontrolled CSOs discharging throughout the catchment, which led to a more complex set of settings necessary to reduce the total CSO volumes. This is typified by a changing prediction of the most relevant actuators, especially when a limited (up to four actuators) were included, though still evident when the maximum number of actuators considered here (8) were included (Figure 11). This changing of the most relevant actuators led to frequent changes in the pump settings, a UDS behavior that is often undesirable and optimized against in an RTC context (Mounce et al., 2020; Sun et al., 2020). This dynamic was also evident in the other large rainfall events, meaning this might be an inherent attribute of the proposed HAPPy procedure. Safeguards against this have to be included in future modifications and are a shortcoming of the proposed procedure. Future work should examine the potential to improve this behavior through the selection of the actuators or by including a set-point change penalty within the optimization function. The development of these safeguards, however, is deemed outside the scope of this work.

Local CSO reductions were especially pronounced when multiple actuators affecting the same part of a cascade were selected in the optimization procedure also visible in the continuous improvement when multiple actuators are included. Utilizing this increased potential of interactions between pumps in the same cascade more efficiently, by changing the actuator selection procedure, could be a future improvement of the HAPPy procedure, but would require a redesign of the selection procedure.

Although the analysis of these two events gave an insight into the potential role of the number of actuators on the performance of the HAPPy procedure, the heterogeneity in results and dominant dynamics of the influence

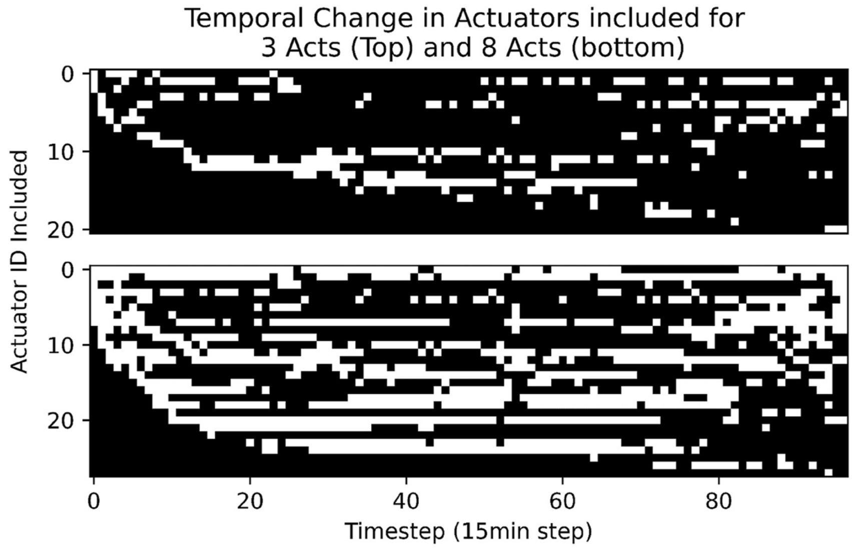


Figure 11. Temporal changes on the actuator IDs which are included in the HAPPy procedure (indicated by white) for the run with the three actuators included (top figure) and eight actuators (bottom figure).

suggests a high level of case-study and rainfall dynamic specificity. The ability of the HAPPy to optimize different UDS, however, shows a level of transferability of the principles behind the HAPPy. Further testing on additional rainfall events and other case studies to better understand the potential of the HAPPy procedure are necessary to quantify and further understand the performance.

5. Conclusions and Future Work

This work proposes a new HAPPy for the near-optimal RTC of large UDS. The HAPPy utilizes a set of offline determined characteristics to optimize the actuators of an UDS with the highest level of impact. This procedure can reduce computational costs through search space reduction without significant performance loss.

Based on the results presented here, the following conclusions can be drawn:

- Selecting only a few actuators within a UDS and optimizing the set points of those in real-time ensured near-global optimal operation of a smaller UDS, with only a minor performance loss when compared to a full-scale MPC-based RTC for both catchments tested. Dynamically selecting those actuators following the proposed procedure showed a better control performance when compared to both the RTC with statically selected actuators and the heuristic rule-based RTC;
- For larger catchments, the relevance of actuators for the performance of RTC procedures varies between and during rainfall events. The rank of the impactfulness of the actuators can be assessed using a global sensitivity analysis and predicted using machine learning techniques such as Random Forest used here. This allows for the effective reduction in the optimization search space by selecting which actuator should be included in the optimization procedure. In turn, this allows large real-life RTC challenges to be addressed;
- The number of actuators included in the HAPPy procedure impacts the outcome. For smaller, spatially heterogeneous events, a critical number of included actuators can be observed: the breaking point. Including at least this critical number of actuators within the procedure ensures the most optimal functioning of the HAPPy approach;
- The performance potential of the HAPPy procedure for rainfall events with a high total rainfall depth increases with the inclusion of additional actuators but seems to level out after approximately 15% of the total number of available actuators are used. The selection of the most relevant actuators during these rainfall events, however, was more spurious, leading to potentially undesirable frequent changes in the settings of the actuators during the optimization.

Although the initial results and conclusions indicate the potential of the HAPPy procedure, several key points should be addressed prior to implementation in a physical UDS. The relative influence of rainfall forecast and model uncertainty on the performance of the HAPPy procedure compared to conventional MPC procedures has to be determined. A key aspect of the proposed procedure is the reduction of model uncertainties induced through oversimplification and linearization of the internal-MPC model. However, the double reliance on rainfall forecasts within the HAPPy procedure (used as an input for both the real-time optimization and the actuator selection algorithm) may lead to a decrease in the UDS performance. Understanding these trade-offs is a key part of the further development of the procedure. Robustness against actuator failure and the long-term validity of the predictive algorithms and optimization are other aspects that should be explicitly understood.

As the work here highlights the ability of MPC to co-optimize the operation of the UDS with heuristic control, inclusion of a HAPPy-based procedure to optimize part of the UDS during failure events (loss of communication between the central decision makers and the local implementation) could be an effective method to improve the fault-tolerance of implemented MPC methods. Work investigating how to implement a HAPPy-based fail-safe would be required. Further optimization of the HAPPy procedure, by changing the actuator selection procedure from a binary to a numerical prediction algorithm, could further improve the function of the HAPPy procedure. Comparison between the HAPPy procedure and distributed, decentralized and local RTC procedures would also give a better insight into the potential use of the proposed methodology.

Acronyms

aRPI	Absolute realized potential indicator
CBA	Central basin approach
CSO	Combined sewer overflow
DT	Decision tree
GA	Genetic algorithm
GSA	Global sensitivity analysis
HAPPy	Heuristic and predictive policy
LP	Linear programming
MLR	Multi-linear regression
MPC	Model predictive control
RB-RTC	Rule-based real-time control
RTC	Real-time control
SSAO	Statically selected actuators optimization
UDS	Urban drainage system
WWTP	Wastewater treatment plant

Data Availability Statement

Rainfall data used in this research is available from the KNMI website (dataplatform.knmi.nl). Models are 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 license https://matplotlib.org/. Models were made in the EPA SWMS 5 open-source software, using the PySWMM python interface, available under the license at https://www.pyswmm.org/citing. Furthermore, the SWMM API interface was used for interacting with the SWMM input files, using the MIT License at https://pypi.org/project/swmm-api/ (Pichler, 2022).

Acknowledgments

The authors would like to extend their gratitude to Gemeentewerken Rotterdam for providing the data and Imber Advies for preparing the InfoWorks models that the models used in this study were based on. This work was done as part of the "*Knowledge Programme Urban Drainage*" and would like to thank the partners of the programme for their continued support: ARCADIS, Deltares, Evides, Gemeente Almere, Gemeente Arnhem, Gemeente Breda, Gemeente 's-Gravenhage, Gemeentewerken Rotterdam, Gemeente Utrecht, GMB Rioleringstechniek, KWR Watercycle Research Institute, Royal HaskoningDHV, Stichting RIONED, STOWA, Sweco, Tauw, vandervalk+degroot, Waterboard De Dommel, Waternet and Witteveen&Bos.

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

Alves, A., Sanchez, A., Vojinovic, Z., Seyoum, S., Babel, M., & Brdjanovic, D. (2016). Evolutionary and holistic assessment of green-grey infrastructure for CSO reduction. *Water*, *8*(9), 402. https://doi.org/10.3390/w8090402

Bachmann-Machnik, A., Brüning, Y., Bakhshipour, A. E., Krauss, M., & Dittmer, U. (2021). Evaluation of combined sewer system operation strategies based on highly resolved online data. *Water*, *13*(6), 751. https://doi.org/10.3390/w13060751

Benedetti, L., Batstone, D. J., De Baets, B., Nopens, I., & Vanrolleghem, P. A. (2012). Uncertainty analysis of WWTP control strategies made feasible. *Water Quality Research Journal*, *47*(1), 14–29. https://doi.org/10.2166/wqrjc.2012.038

Dirckx, G., Schutze, M., Kroll, S., Thoeye, C., De Gueldre, G., & Van De Steene, B. (2011). Cost-efficiency of RTC for CSO impact mitigation. *Urban Water Journal*, *8*(6), 367–377. https://doi.org/10.1080/1573062X.2011.630092

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

Eulogi, M., Ostojin, S., Skipworth, P., Shucksmith, J. D., & Schellart, A. (2020). Hydraulic optimisation of multiple flow control locations for the design of local real time control systems. *Urban Water Journal*, *18*(2), 91–100. https://doi.org/10.1080/1573062X.2020.1860238

Fletcher, T. D., Shuster, W., Hunt, W. F., Ashley, R., Butler, D., Arthur, S., et al. (2014). SUDS, LID, BMPs, WSUD and more—The evolution and application of terminology surrounding urban drainage. *Urban Water Journal*, *12*(7), 525–542. https://doi.org/10.1080/1573062X.2014.916314

Garcia, L., Barreiro-Gomez, J., Escobar, E., Tellez, D., Quijano, N., & Ocampo-Martinez, 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

Garofalo, G., Giordano, A., Piro, P., Spezzano, G., & Vinci, A. (2017). A distributed real-time approach for mitigating CSO and flooding in urban drainage systems. *Journal of Network and Computer Applications*, *78*, 30–42. https://doi.org/10.1016/j.jnca.2016.11.004

Geerse, J. M., & Lobbrecht, A. H. (2002). Assessing the performance of urban drainage systems: General approach applied to the city of Rotterdam. *Urban Water*, *4*(2), 199–209. https://doi.org/10.1016/s1462-0758(02)00017-1

Giordano, A., Spezzano, G., Vinci, A., Garofalo, G., & Piro, P. (2014). A cyber-physical system for distributed real-time control of urban drainage networks in smart cities. In *Internet and distributed computing systems: 7th international conference, IDCS 2014* (Vol. 7, pp. 87–98). Springer International Publishing.

Jorgensen, M., Schilling, W., & Harremoes, P. (1995). General assessment of potential CSO reduction by means of real time control. *Water Science and Technology*, *32*(1), 249–257. https://doi.org/10.1016/0273-1223(95)00562-2

Joshi, P., Leitão, J. P., Maurer, M., & Bach, P. M. (2021). Not all SuDS are created equal: Impact of different approaches on combined sewer overflows. *Water Research*, *191*, 116780. https://doi.org/10.1016/j.watres.2020.116780

Kändler, N., Annus, I., & Vassiljev, A. (2022). Controlling peak runoff from plots by coupling street storage with distributed real time control. *Urban Water Journal*, *19*(1), 97–108. https://doi.org/10.1080/1573062x.2021.1958235

Kroll, S., Weemaes, W., Van Impe, J., & Willems, P. (2018). A methodology for the design of RTC strategies for combined sewer networks. *Water*, *10*(11), 1675. https://doi.org/10.3390/w10111675

Liang, R., Thyer, M. A., Maier, H. R., Dandy, G. C., & Di Matteo, M. (2021). Optimising the design and real-time operation of systems of distributed stormwater storages to reduce urban flooding at the catchment scale. *Journal of Hydrology*, *602*, 126787. https://doi.org/10.1016/j.jhydrol.2021.126787

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*.

Ledergerber, J. M., Maruéjouls, T., & Vanrolleghem, P. A. (2020). No-regret selection of effective control handles for integrated urban wastewater systems management under parameter and input uncertainty. *Water Science and Technology*, *81*(8), 1749–1756. https://doi.org/10.2166/wst.2020.144

Lougee-Heimer, R. (2003). The common optimization interface for operations research: Promoting open-source software in the operations research community. *IBM Journal of Research and Development*, *47*(1), 57–66. https://doi.org/10.1147/rd.471.0057

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

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

Mintenig, S. M., Int-Veen, I., Loder, M. G. J., Primpke, S., & Gerdts, G. (2017). Identification of microplastic in effluents of waste water treatment plants using focal plane array-based micro-Fourier-transform infrared imaging. *Water Research*, *108*, 365–372. https://doi.org/10.1016/j.watres.2016.11.015

Mollerup, A. L., Mikkelsen, P. S., & Sin, G. (2016). A methodological approach to the design of optimising control strategies for sewer systems. *Environmental Modelling & Software*, *83*, 103–115. https://doi.org/10.1016/j.envsoft.2016.05.004

Montes, C., Kapelan, Z., & Saldarriaga, J. (2021). Predicting non-deposition sediment transport in sewer pipes using Random forest. *Water Research*, *189*, 116639. https://doi.org/10.1016/j.watres.2020.116639

Mounce, S. R., Shepherd, W., Ostojin, S., Abdel-Aal, M., Schellart, A. N. A., Shucksmith, J. D., & Tait, S. J. (2020). Optimisation of a fuzzy logic-based local real-time control system for mitigation of sewer flooding using genetic algorithms. *Journal of Hydroinformatics*, *22*(2), 281–295. https://doi.org/10.2166/hydro.2019.058

Naughton, J., Sharior, S., Parolari, A., Strifling, D., & McDonald, W. (2021). Barriers to real-time control of stormwater systems. *Journal of Sustainable Water in the Built Environment*, *7*(4), 04021016. https://doi.org/10.1061/jswbay.0000961

Oh, J., & Bartos, M. (2023). Model predictive control of stormwater basins coupled with real-time data assimilation enhances flood and pollution control under uncertainty. *Water Research*, *235*, 119825. https://doi.org/10.1016/j.watres.2023.119825

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

Pichler, M. (2022). SWMM API (Version 0.3). Retrieved from https://gitlab.com/markuspichler/swmm_api

Pleau, M., Colas, H., Lavallee, P., Pelletier, G., & Bonin, R. (2005). Global optimal real-time control of the Quebec urban drainage system. *Environmental Modelling & Software*, *20*(4), 401–413. https://doi.org/10.1016/j.envsoft.2004.02.009

Quaranta, E., Fuchs, S., Liefting, H. J., Schellart, A., & Pistocchi, A. (2022). Costs and benefits of combined sewer overflow management strategies at the European scale. *Journal of Environmental Management*, *318*, 115620. https://doi.org/10.1016/j.jenvman.2022.115629

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 algorithm in urban drainage modelling. *Urban Water*, *1*(1), 79–89. https://doi.org/10.1016/S1462-0758(99)00010-2

Rieckermann, J., Anta, J., Scheidegger, A., & Ort, C. (2011). Assessing wastewater micropollutant loads with approximate Bayesian computations. *Environmental Science and Technology*, *45*(10), 4399–4406. https://doi.org/10.1021/es1030432

10.1029/2022WR033854

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.

Saagi, R., Kroll, S., Flores-Alsina, X., Gernaey, K. V., & Jeppson, U. (2018). Key control handles in integrated urban wastewater systems for improving receiving water quality. *Urban Water Journal*, *15*(8), 790–800. https://doi.org/10.1080/1573062X.2018.1547771

Sadler, J. M., Goodall, J. L., Behl, M., Morsey, M. M., Culver, T., & 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., Erbe, V., Haas, U., Scheer, M., & Weyand, M. (2008). Sewer system real-time control supported by the M180 guideline document. *Urban Water Journal*, *5*(1), 67–76. https://doi.org/10.1080/15730620701754376

Sun, C., Svensen, J. L., Borup, M., Puig, V., Cembrano, G., & Vezzaro, L. (2020). An MPC-enabled SWMM implementation of the Astlingen RTC benchmarking network. *Water*, *12*(4), 1034. https://doi.org/10.3390/w12041034

Svensen, J. L., Sun, C., Cembrano, G., & Puig, V. (2021). Chance-constrained stochastic MPC of Astlingen urban drainage benchmark network. *Control Engineering Practice*, *115*, 104900. https://doi.org/10.1016/j.conengprac.2021.104900

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

Van Daal-Rombouts, P. M. M., Sun, S., Langeveld, J. G., Bertrand-Krajewski, J.-L., & Clemens, F. H. L. R. (2016). Desing and performance evaluation of a simplified dynamics 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 in 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 combined sewer systems: A review of performance and influencing factors. *Water Science and Technology*, *85*(4), 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*, *617A*, 128900. https://doi.org/10.1016/j.jhydrol.2022.128900

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

Vezzaro, L., & Grum, M. (2014). A generalised overflow risk assessment (DORA) for real time control of urban drainage systems. *Journal of Hydrology*, *515*, 292–303. https://doi.org/10.1016/j.jhydrol.2014.05.019

Weinreich, G., Schiling, W., Birkley, A., & Moland, T. (1997). Pollution based real time control strategies for combined sewer systems. *Water Science and Technology*, *36*(8–9), 331–336. https://doi.org/10.1016/S0273-1223(97)00577-5