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The Effect of Uncertainties on the Performance of Real-Time Control of Urban Drainage Systems

The Effect of Uncertainties on the Performance of Real-Time Control of Urban Drainage Systems

Proefschrift

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aan de Technische Universiteit Delft,
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door

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CONTENTS

SUMMARY

REAL-time control (RTC) is a technique used to dynamically control urban drainage systems to utilise the existing infrastructure more optimally. It can be used to achieve a number of objectives aiming to improve the functioning of the urban drainage system, typically through the reduction of pollution. When heavy rainfall occurs, combined sewer systems (CSSs) can cause combined sewer overflows (CSOs) to discharge diluted, yet untreated, wastewater into receiving water bodies. These discharges can lead to ecological damage and pose a public health hazard, resulting in more stringent legislation necessitating the reduction of CSO discharges. To achieve this, expensive upgrades to the urban drainage system (UDS) have traditionally been used. RTC can reduce or negate the need for these expensive upgrades by fully utilising the existing infrastructure. RTC increasingly relies on more complex algorithms and data streams due to the rise of cheaper computing power and sensors, leading to a better understanding of the systems and more potential for dynamic optimisation. Uncertainties (inherent to modelling and monitoring exercises) can affect the functioning of these RTC procedures, but the influence of uncertainty on the performance of RTC procedures is poorly understood. This is an often quoted reason against the implementation of RTC strategies as a whole. The aim of this thesis is therefore to increase the understanding of how uncertainties can affect the performance of RTC procedures. Using three case studies (urban drainage systems of WWTP Eindhoven, Hoogvliet and Dokhaven) and both heuristic and real-time optimisation procedures, this aim was assessed.

Firstly, an unbiased metric had to be developed to allow for the accurate quantification of the *performance* of an RTC strategy. It was found that using a 'non-RTC' or 'pre-RTC' baseline to assert performance improvement through RTC was insufficient, as both baselines can artificially inflate the RTC performance by comparing to a potentially non-intended and sub-optimal functioning of the UDS. Additionally, it does not consider the physical limitations imposed on an RTC strategy through the UDS characteristics. For these reasons, a single-input single-output optimised static heuristic baseline (where each actuator is given a single set point which is the global optimal setting) was developed. A maximum theoretical performance, which is calculated by iteratively computing the minimum CSO discharge per pumped district, was also developed. These two limits were combined with the performance of the RTC strategy and used to calculate a *realised performance indicator* (bound between $-\infty$ and 1, the latter being the equivalent of RTC realising the full theoretical potential). This metric was developed on the WWTP Eindhoven catchment and shown to be transferable in the application in other catchments.

This metric was then used to assess the functioning of a combined heuristic and predictive policy (HAPPy), a control procedure designed to enable real-time optimisation for catchments with inhibitively many actuators (the UDS of WWTP Dokhaven has over 50 actuators used in the control procedure). The methodology relied on the relative importance of each actuator with regard to the RTC potential, which was chosen to change during and in-between events. This was demonstrated using a set of 150+ global sensitivity analyses. Using this, the most relevant actuators were selected using decision trees, and the settings were optimised using a genetic algorithm. The potential of this method was close to that of a full MPC when applied to the WWTP Hoogvliet case and showed considerable potential for system performance improvement when applied to the WWTP Dokhaven case.

Having established a metric, the influence of various sources of uncertainty on the performance of a full-MPC system (applied to the catchment of Eindhoven) was tested following a model-based approach. Rainfall nowcast (following an applied algorithm from the Dutch Meteorological Institute) was found to have only limited influence on the efficacy of an MPC procedure. Uncertainty in the boundary conditions (downstream WWTP or pumping capacity) and model-related uncertainties (caused by the simplification of the system), on the other hand, induced a significant reduction in RTC efficacy, leading to (in some cases) performance worse compared to the aforementioned static baseline. For this reason, two forms of risk were identified: risk of relative performance loss (where the RTC still improves the functioning of the UDS, but less than projected) and risk of operative deterioration (whereby the UDS functions worse compared to a static baseline). No superimposition of the risks from various sources was found.

Conversely, rainfall nowcast, when used to enhance the functioning of heuristic control strategies, can lead to both risks of relative performance loss and operative deterioration. The nowcast accuracy, however, was found to depend on various rainfall characteristics, which can be leveraged to design nowcast-informed heuristic control procedures with limited risks for performance loss. 6 nowcast-informed heuristic procedures were developed and applied to the WWTP Dokhaven case, all showing theoretical potential for UDS performance improvement. The procedure relying on the prediction of the end of the event was, however, the only one to improve the functioning of the system with both perfect and real forecasts, owing to the relative accuracy of this aspect of the rainfall nowcast.

The uncertainties causing a bias within the model were previously shown to be the most influential on the performance of real-time optimisation procedures. These biases can be exacerbated when transitions occurring in the urban environment are not applied to the underlying model. To assess the long-term functioning of RTC procedures in relation to urban transitions, various scenarios were applied to the Eindhoven and Hoogvliet case studies. In the case of widespread application of blue-green infrastructure, an exponential decrease in the relative performance (the ratio between 'achieved' RTC performance and RTC potential) was observed for an optimised heuristic procedure. An MPC procedure was equally affected, leading to the need for re-calibration of the internal-MPC model when significant changes in the runoff (here, around 10-15% reduction was a critical point) are observed. However, no consistency in the response between different catchments was found, meaning the influence of long-term transitions is highly case-study dependent.

Thus, uncertainties inherently present in RTC strategies can significantly affect the function of Real-Time Control strategies. This is the case for both heuristic and real-time optimisation procedures and can be exacerbated by long-term transitions if they are not accounted for. Understanding these influences should be a key part in the design of implementable control techniques, to ensure the expected functioning is achieved without significant risks of performance loss.

Samenvatting

Real-time sturing is een techniek die toegepast kan worden om een rioleringssysteem zo te sturen dat de bestaande infrastructuur optimaal benut wordt. Het kan gebruikt worden om een aantal doelen, waarmee het functioneren van het rioleringssysteem verbeterd wordt, te bereiken. Het voornaamste doel is het reduceren van verontreiniging vanuit het stedelijke afvalwatersysteem. Wanneer zware regen voorkomt, kunnen gemengde rioolsystemen dermate belast worden dat overstorten plaatsvinden, waarbij verdund, maar ongezuiverd, afvalwater in oppervlakte water wordt geloosd. Deze lozingen kunnen leiden tot ecologische schade en gezondheidsproblematiek, wat tot striktere regulaties leidde die het verder reduceren van overstorten noodzakelijk maken. Om dit te bewerkstelligen, worden dure aanpassingen aan het bestaande rioleringssysteem gedaan. Real-time sturing kan de noodzaak tot deze dure aanpassingen verminderen of helemaal wegnemen door middel van het optimaal gebruiken van de bestaande infrastructuur. Real-time sturing maakt, in steeds meerdere mate, gebruik van complexe algoritmes en grote hoeveelheden data. Dit komt voort uit de groei van goedkope sensoren en groeiende rekenkracht, die hebben geleid tot een beter begrip van het dynamische gedrag van rioleringssystemen en meer potentie voor real-time optimalisatie. Onzekerheden, die inherent verbonden zijn aan modellen en de meetkunde), kunnen een effect hebben op het functioneren van deze real-time sturingsprocedures. Het effect van onzekerheden worden nog niet goed begrepen, en dit wordt vaak als argument tegen de implementatie van real-time sturing gebruikt. Het doel van dit proefschrift is daarom om de effecten van onzekerheden op de prestatie van real-time sturing beter te begrijpen. Drie casussen (de rioleringssystem van afvalwaterzuiveringen Eindhoven, Hoogvliet en Dokhaven) en zowel heuristische als real-time optimalisatie sturingsprocedures zijn gebruikt om dit doel te halen.

Hiervoor moest eerst een indicator ontwikkeld worden zodat de prestatie van een sturingsstrategie zonder stelselmatige invloed nauwkeurig gekwantificeerd kan worden. Het gebruik van een “pre-sturing” of “zonder sturing” als vergelijkingspunt waartegen de prestatie van de sturing gemeten kan worden was niet genoeg bevonden, gezien beide vergelijkingspunten kunstmatig de prestatie kunnen overdrijven door een vergelijking te maken met een suboptimaal functionerend rioleringssysteem. Daarnaast worden de fysieke limieten van de potentie van een sturingssysteem niet meegenomen. Om deze redenen werd een geoptimaliseerde één-input één-output heuristisch vergelijkingspunt ontwikkeld, waarbij elke actuator in het rioleringssysteem één globaal optimaal instelpunt heeft, afhankelijk van één input. Ook werd een theoretische maximumprestatie ontwikkeld, die wordt berekend door iteratief de minimale overstortlozing per gepompt district te berekenen. Deze twee grenswaarden werden gecombineerd met de prestaties van de sturingsstrategie en gebruikt om een indicator voor de gerealiseerde prestaties te berekenen (welke tussen de $-\infty$ en 1 ligt, waarbij 1 staat voor een sturingsstrategie die de gehele sturingspotentie van een rioleringssysteem benut). Deze indicator is ontwikkeld op het rioleringssysteem van AWZI Eindhoven en is overdraagbaar gebleken bij de toepassing in andere rioleringssystemen.

Deze indicator werd vervolgens gebruikt om het functioneren van een gecombineerd heuristisch en voorspellende sturing (heuristic and predictive policy: HAPPy) te beoordelen. Dit is een sturingsprocedure die is ontworpen om real-time optimalisatie mogelijk te maken voor rioleringssystemen waarbij er te veel actuatoren aanwezig zijn (het rioleringssysteem van AWZI Dokhaven heeft meer dan 50 pompen die sturing technisch relevant zijn. De methodologie maakt gebruik van de relatieve invloed die elke actuator heeft op het behalen van het sturingsdoel, een invloed die tijdens een bui verandert. Deze verandering van invloed werd aangetoond aan de hand van een reeks van meer dan 150 gevoeligheidsanalyses. Op basis hiervan werden de meest relevante actuatoren dynamisch geselecteerd met behulp van beslissingsbomen, en werden de instelling geoptimaliseerd met behulp van een genetisch algoritme. Het potentieel van deze methode lag dicht bij dat van andere real-time optimalisatie methodes bij de toepassing op AWZI Hoogvliet en toonde een aanzienlijke verbetering in het functioneren van het rioleringsstelsel van AWZI Dokhaven.

Gebruikmakende van de eerder genoemde indicator werd de invloed van verschillende bronnen van onzekerheid op de prestaties van een volledig real-time optimalisatie systeem (toegepast op het rioleringsstelsel van AWZI Eindhoven) getest. Voorspelling van neerslag (verkregen via een toegepast algoritme van het Nederland Meteorologisch Instituut) bleek slecht een beperkte invloed te hebben op de prestatie van real-time optimalisatie procedures. Echter, onzekerheden in de randvoorwaarden (de benedenstroomse AWZI capaciteit of rioleringspomp capaciteit) en model gerelateerde onzekerheden (veroorzaakt door de vereenvoudiging van het rioleringssysteem) leidden tot een aanzienlijke vermindering van de doelmatigheid van de sturing, waardoor de prestatie (in sommige gevallen) onder dat van de bovengenoemde statische vergelijkingspunten viel. Hierdoor werden twee vormen van risico's geïdentificeerd: het risico tot relatief prestatieverlies (waarbij de sturing het functioneren van het rioleringssysteem verbetert, maar in mindere mate dan verwacht) en het risico van operationele achteruitgang (waarbij het systeem slechter functioneert in vergelijking tot de statische vergelijkingspunten). Er werd geen superpositie van de onzekerheden op de risico's gevonden.

Omgekeerd kan de voorspelling van regenval, wanneer het wordt gebruikt om de werking van heuristische sturing te verbeteren, zowel tot risico's op relatief prestatieverlies als tot operationele achteruitgang leiden. De nauwkeurigheid van de voorspelling hing af van verschillende neerslagkenmerken, die kunnen worden benut om voorspelling-geïnformeerde heuristische sturing te ontwerpen met beperkte risico's. Er werden 6 van dit soort sturingsprocedures ontwikkeld en toegepast op de casus van AWZI Dokhaven. Al deze sturingsprocedures hadden een theoretisch potentieel vertoond voor de verbetering van het functioneren van het rioleringssysteem. De procedure die uitgaat van de voorspelling van het einde van de regenval was echter de enige die het functioneren van het rioleringssysteem verbeterde met zowel perfect als echte voorspellingen, vanwege de relatieve nauwkeurigheid van dit aspect van de regenvoorspellingen.

De onzekerheden die leiden tot stelselmatige onder of overschatting van de model resultaten hebben de grootste invloed op de prestaties van real-time optimalisatieprocedures. Deze vertekeningen kunnen worden versterkt wanneer transities die voorkomen in de stedelijke omgeving niet regelmatig worden toegepast op het onderliggende model. Om het functioneren van sturingsprocedures op lange termijn te beoordelen, zijn verschillende transitie-scenario's toegepast op de casussen van Eindhoven en Hoogvliet. In het geval van grootschalige toepassing van blauw-groene infrastructuur werd voor een geoptimaliseerde heuristische procedure een exponentiele afname van de relatieve prestatie (de verhouding tussen de "bereikte" sturingsprestatie en het sturingspotentieel) waargenomen. Een real-time optimalisatie procedure werd eveneens beïnvloed, waardoor het onderliggende model opnieuw moet worden gekalibreerd wanneer een significante verandering in de afvloeiing word waargenomen (hier was een vermindering van rond de 10-15% kritiek). Er werd echt geen consistentie in de respons tussen verschillenden rioleringssystemen gevonden, wat betekent date de invloed van langetermijnovergangen in hoge mate afhankelijk is van de casus.

De onzekerheden die inherent zijn aan sturing strategieën kunnen de werking van real-time sturing aanzienlijk beïnvloeden. Dit is het geval voor zowel heuristische als real-time optimalisatieprocedures en kan worden verergerd door lange-termijnovergangen indien er geen rekening mee wordt gehouden. Inzicht in deze invloeden moet een belangrijk deel vormen van het ontwerp van implementeerbare sturingstechnieken, om ervoor te zorgen dat de verwachte werking wordt bereikt zonder aanzienlijke risico's op prestatieverlies.

1
INTRODUCTION

1.1. URBAN WATER

URBAN areas demand clean drinking water to provide for the population, industry and commercial activities. When this water is used, it becomes polluted, containing pathogens, high levels of organic material, nutrients, heavy metals, micro-pollutants and micro-plastics. Within the urban water cycle, urban drainage systems (UDS) play a critical role in ensuring public safety by conveying this wastewater to a wastewater treatment plant (WWTP) or, at a minimum, away from the population.

The high level of imperviousness associated with urban areas, furthermore, means that the infiltration of rainfall water is inhibited. A large percentage of the rainfall is therefore converted into runoff, which has to be transported to avoid local flooding (which would cause significant damage and public health issues). Wastewater and urban runoff can be conveyed through a single set of conduits, known as a combined sewer system (CSS) or independently, through a separate sewer system (SSS). Due to the comparatively lower installation costs of CSS, these are the most found form of sewer system installed in Europe. In the Netherlands, roughly 65% of the total length of sewer systems falls under the CSS type (equating to around 50,000km of piped networks servicing 957,000,000m^2, see RIONED (2016)), although globally a clear shift away from CSS is noted when replacing an existing system or building new urban areas (Tibbetts, 2005).

During dry weather conditions and rain events below the static capacity of the UDS, CSS convey the combined flow of water to a WWTP, where the flow is treated and discharged into receiving water bodies. When the UDS capacity (the in-sewer storage plus the capacity of the WWTP) is exceeded, the combination of wastewater and runoff is discharged through *combined sewer overflows* (CSOs), leading to the release of wastewater (including the aforementioned pollutants) into the receiving water bodies. The objective of these CSO structures in the UDS is to minimise flooding of the populated streets with wastewater, which would otherwise result from the overloading of the CSS.

1.1.1. WATER QUALITY ISSUES

The Water Framework Directive (EC, 2000), the key European regulation covering surface water quality, calls for member states to reach *good* water quality by 2027, regarding physical, chemical and biological parameters. Although the legislation marks a key shift towards integrated water management (Kallis, 2001), it has been criticised as being overly ambitious (Hering et al., 2010), and vague in its methodological approach (van

Kats et al., 2022). In an inventory, Dutch surface waters still rank below the required *good* status in over 95% of the cases (at the time of writing) given the latest data available. Given this, reducing the pollution loads from publicly owned spaces should be prioritised, as there is a pre-existing strong regulatory framework to do so.

The CSOs discussed in the previous section cause significant pollution to the water quality around and in urban areas. Using a modelling approach, it is estimated that for 671 urban areas in the European Union, the total CSO volume is close to 6bln m^3yr^{-1}, causing roughly 463mln m^3yr^{-1} of raw wastewater to be discharged (Quaranta et al., 2022). Considering two key nutrients (which can cause eutrophication of receiving waters), ammonia (NH_3) and phosphorous (P), and using the medium concentration in wastewater for both (45 and 15mgL^{-1} respectively (Henze et al., 2008)), this leads to total annual loads of 20,800 and 7,000 tons respectively. It should be noted that the pollution loads transported are highly heterogeneous (Li & Vanrolleghem, 2022) and affected by the local dynamics at the CSO location (Quijano et al., 2017). These emissions can have potentially detrimental results to the local receiving water ecology and public health implications (Owolabi et al., 2022).

More pressingly compared to the nutrients, CSOs can cause a significant increase in local biological and chemical oxygen demand (BOD and COD) leading to anoxic or low oxygen conditions in the receiving water bodies (Even et al., 2004; Hvitved-Jacobsen, 1982; Miskewitz & Uchrin, 2013). This can lead to (non-reversible) ecological degradation and is a common improvement objective for decision makers (Langeveld et al., 2013). Public health issues, caused by the release of pathogenic material, can occur directly as a result of CSO emissions (McGinnis et al., 2018; Sojobi & Zayed, 2022). These effects can have a significant influence on public health issues further kilometres downstream (Sterk et al., 2016), increasing the risk of exposure to the public and highlighting the necessity of decreasing CSOs as much as possible.

Micro-pollutant emissions (which are of increasing concern due to better understood adverse effects on human and ecological health as well as bio-accumulation potential (Cantoni et al., 2020; Schwarzenbach et al., 2006; Thornber et al., 2022)), are dominated by direct emission from the sewer and treatment plants alike. Over 99.75% of the diclofenac (anti-inflammation drug), metoprolol ($\beta-$blocker) and carbamazepine (anticonvulsant) loads to surface waters were found to be directly discharged through the urban wastewater system (Emissieregistratie, 2022; Van der Hoek et al., 2013)

In the case of phosphorous emissions, the contribution of CSO emissions to the total load might seem negligible. In the Netherlands, an estimated 0.1% of the total P emissions to surface waters originate directly from the sewer systems. However, on a local level, these discharges to receiving waters (which can potentially be small in size and flow relative to the pollutant loading and are therefore more vulnerable to pollutant discharges) can be closer to populated areas compared to the discharge points of WWTPs, making their relative contribution to ecological and human health risks more pronounced and their mitigation arguably more important.

Indeed, the concept version of the new European Urban Wastewater Treatment Directive (UWWTD, EC (2022)) calls for the widespread implementation of measures to reduce all pollution from the urban wastewater systems, with particular emphasis on the increased treatment against micro-pollutants and best-practice management against '*traditional*' pollutants. When additional investments are done to the treatment capacity, the impact of CSOs will become relatively more significant and methods to alleviate the pollution loads through these should be further developed.

1.2. WATER QUALITY SOLUTIONS

To minimise the impact of UDS on the receiving water bodies, several methods have already been proposed and implemented. Foremost, driven by direct (in the case of Flanders through VMM (1995)) or indirect (in the case of the USEPA (2000)) legislation, separation of the wastewater and urban runoff is one of the key strategies and has been a preferred strategy for a long time (Tarr, 1979). This will reduce untreated wastewater discharges by no longer mixing the two water streams (urban runoff and wastewater), therefore directly reducing the nutrient, pathogen and pharmaceuticals and personal care products (PPCP) fraction of the pollution (as these pollutants originate from wastewater as opposed to urban runoff). There are some drawbacks though, particularly costs (SSS are roughly 50% more expensive compared to CSS (RIONED, 2021a)) and the lack of treatment of the urban runoff, causing discharges of heavy metals and other pollutants (Boni et al., 2022; De Toffol et al., 2007; Mutzner et al., 2022). The latter can be (partially) mitigated through the implementation of *improved separated sewer systems*, whereby part of the urban runoff is still transported to the treatment plant. Though again, considerable additional costs are associated with these systems.

The expansion of the existing CSS through the addition of settling tanks is another commonly applied 'grey' (referring to concrete solutions) technique for CSO emission reduction. These tanks are retro-fitted in (optimised) existing CSS to provide additional storage to avoid and reduce CSO events and to allow for the sedimentation of the solid pollution load (Bertrand–Krajewski et al., 2002; Carbone et al., 2015; Field & O Connor, 1997). The city of Graz, Austria, for example, constructed a Central Storage Tunnel (see Figure 1.1a) with a total retention volume of 91,000 m^3 at a price of EUR 81.4 mln (meaning a cost of below EUR 900 per m^3). This is on the low end of the estimated EUR 810-2,670 m^3 usually quoted for settling tank solutions (RIONED, 2021b).

The last static solution, which has gained increased popularity over the last decades, is the implementation of Blue-Green (BG) infrastructure (Fletcher et al., 2015). Although these solutions can take many forms, their main objective is to retain and infiltrate as much urban runoff as possible, thereby reducing the inflow to the drainage system and returning the urban area to a more pre-urbanised hydrological cycle. Cities with high implementation levels of BG infrastructure have been referred to as *sponge cities* in China (Zevenbergen et al., 2018) and full infiltration of the rainfall is an often cited objective of waterboards in the Netherlands (WDD, 2022). Along with the water quality and quantity benefit of BG infrastructure, they contribute to increased livability of an area, air pollution mitigation, local ecological benefits and urban heat mitigation (Probst et al., 2022) (known under the umbrella of *co-benefits* (Alves et al., 2020)), making this solution more attractive. Their application, however, can be hindered by local groundwater level concerns (Ghofrani et al., 2017) and spatial constraints. Furthermore, little is known about the long-term functioning and asset management needs for this type of solution (Langeveld et al., 2022a; Vollaers et al., 2021).

(a) (b)

Figure 1.1: Examples of UDS improvement for CSO reduction with (a) an example of a stormwater tank, taken from the Graz sewer system and (b) a filled WADI at the Delft University of Technology Campus.

All the aforementioned static improvements to the urban drainage system to alleviate water quality concerns can be costly (even when optimised) and constrained by spatial limitations. This is particularly applicable when considering existing urban areas and to a lesser extent to new-build areas (where BG infrastructure is more frequently used to convey runoff). Recently, the new UWWTD (in concept version (post-consultation phase) at the point of writing) calls, through Article 8, for another solution: the more widespread improvement of the use of existing drainage infrastructure:

"*[...] Therefore, the measures to be considered should be based on a thorough analysis of the local conditions and should favour a preventive approach aiming at limiting the collection of unpolluted rainwater and* ***optimising the use of existing infrastructure*** *[...]*"

The optimisation which Article 8 refers to can be interpreted to apply to both the retro-fitting/rehabilitation *and* operation of the UDS. Dynamically operating the CSS, known as Real-Time Control (RTC), has been shown to decrease pollution loads from UDS and has been applied in various forms since the 1960s in the United States and Europe alike (Borsányi et al., 2008). RTC functions through the adjustment of the actuators (in the context of UDS, these are mainly (frequency-controlled) pumps, moveable weirs and orifices), based on the real-time observation of the system-state (Schütze et al., 2004) to achieve a certain pre-set objective (CSO volume reduction, CSO pollutant load reduction, energy consumption reduction and receiving water impact reduction are the most commonly used). These adjustments to the system actuator settings enable the dynamic distribution of the water in the system, therefore (in theory) ensuring that all redundant system capacity is used before CSO spills occur, especially when the UDS is heterogeneously loaded (resulting from spatial and temporal heterogeneity of rainfall events). The determination of the set-points of these actuators can be through a variety of methods, which are further highlighted and examined more thoroughly in Chapter 2.

Although a large variety of specific control procedures and strategies exist, they ubiquitously rely on the numerical representation of (part of) the UDS. These models are either used to directly control the UDS (through Model Predictive Control, MPC, in which a simplified model is used to compute the best settings of the actuators for every timestep, see Lund et al. (2018) for a literature review), or used to "experiment" with settings and determine a heuristic procedure (which can also be formally optimised).

1.3. URBAN WATER MODELS

In order to design dynamic solutions, urban water practitioners rely on large monitoring networks and models to understand and operate the UDS. To accurately represent the UDS, models have to be calibrated (although this might not always be the case in practice (Tscheikner-Gratl et al., 2016)) and developed for a particular purpose (Pedersen et al., 2022). With the rise of more powerful computers, the notion of *Digital Twins* (DT), a digital replica containing all information of the UDS, also has taken a foothold within the modelling literature (Pedersen et al., 2021a).

The core of UDS modelling is to accurately represent the hydrodynamics (movement of water) through the system and the emphasis in this thesis will be on this type of model. It should be noted, however, that UDS models can integrate pollution dynamics (see Jia et al. (2021)), WWTP dynamics (Benedetti et al., 2013a) and all other urban water processes (Bach et al., 2014). The hydrodynamics of a UDS can be represented either in a Full-Hydrodynamic (FH) model or through simplified models. Both model types have their respective use within the UDS modelling and are useful in different settings.

FH models describe the hydrodynamics in each individual conduit of the UDS, and are therefore, from a practical point of view, the closest to *DTs* as possible (considering only hydrodynamics). FH models solve the full Saint-Venant equation (usually through a 1-dimensional simplification) for each of the conduits and manholes using various numerical schemes, making the model deterministic in nature. Software packages are available to allow practitioners relatively easy access to FH models. From these software packages, open-source packages such as EPA-SWMM5 (Rossman, 2015) are the most popular in the research community, owing to the transparency and flexibility in the source code (therefore facilitating the development of improvements and additional tools) and lack of licence costs.

Simplified models (or *meta-models* per Garzón et al. (2022), *surrogate models* per Thrysøe et al. (2019) and *conceptual models* per Vaes and Berlamont (1999) and Willems and Berlamont (2002)) are models that, rather than describing the hydrodynamics of each individual conduit within a UDS, take a conceptual approach. This can be in the form of *virtual reservoir modelling* (lumping together the volume of various conduits to form a virtual reservoir, a modelling technique used throughout this thesis) as described by Cembrano (2004), various machine learning techniques (see Garzón et al. (2022) for a comprehensive overview), graph-theory based modelling (Meijer et al., 2018) or other stochastic methods (i.e. Rossi et al. (2005)). In the design of these models, the main trade-off to consider is the accuracy and the computational penalty of the model. Speed-ups (the computational increase factor between FH-model and simplified model) of around 10^6 at a limited cost in accuracy are not uncommon (Vaes & Berlamont, 1999; Wolfs & Willems, 2017). Although these values indicate a high potential for simplified models in urban drainage studies, the additional uncertainties which are introduced through these forms of modelling can be significant.

1.3.1. MODEL UNCERTAINTY

Uncertainties are unavoidable in any modelling activity. As urban wastewater systems regularly span multiple kilometres and are buried away from regular inspection, having perfect knowledge of the entire system is practically impossible. This, in combination with various model parameters which can only be inferred from monitoring or experimental data (weir overflow constants, roughness coefficients, and initial losses to name a few), means that building a sufficiently representative model of an urban wastewater system with limited uncertainties is a laborious, but necessary, task. Equally, quantifying these uncertainties to be able to correctly interpret model outputs requires significant effort (Moreno Rodenas, 2019; Vezzaro et al., 2013).

The uncertainty in the model output depends on the input uncertainty, initial / boundary condition uncertainty and model parameter/model structure uncertainties. In a well-calibrated model, the difference between the model output and 'real' values are normally distributed (Tscheikner-Gratl et al., 2016). The distribution (mean and standard deviation) of this difference depends on the propagation of the five uncertainties mentioned before. An absolute mean difference of these values above zero indicates a bias within the model and should be avoided through careful calibration of the model.

Model uncertainties can be exacerbated by overlooking the speed at which urban areas, and therefore urban water processes, can change and failing to incorporate these within the modelling exercise. Densification, urban expansion but also the implementation of any of the static solutions mentioned in this chapter can change the runoff behaviour of an existing area and urban drainage system. Over the lifespan of a sewer pipe (estimated 60 years), these changes can lead to significantly different wastewater and urban runoff patterns. Using satellite imagery, above-ground changes which can completely transform an urban area can easily be seen (see Figure 1.2 for the changes occurring around the office in which this thesis was written), with obvious implications for the urban hydrology.

To maintain a well-calibrated model, a key tool is needed to ensure robust decision-making processes (Tscheikner-Gratl et al., 2016), therefore means continuous updating of the existing models to ensure accurate representation of the underlying system. However, the calibration of UDS models requires sufficient monitoring data to ensure the validity of various uncertain parameters, which takes time (given the need for rainfall data in the case of CSS or the calibration of a stormwater system). Tools used for the

Figure 1.2: Changes occurring around the Civil Engineering and GeoSciences building from the TU Delft campus, highlighting in red boxes the changes occurring from 2018-2022 (visible on the satellite) in and around the TU Delft campus, thereby spanning the entirety of this PhD Project

automation of the calibration and generation of simplified models have been proposed (Kroll et al., 2017), and similarly, tools for the assimilation of changes in models have been proposed for water reservoir models (Milašinović et al., 2022) but have not been shown to function in practice yet.

1.3.2. REAL-TIME CONTROL, MODELS AND UNCERTAINTIES

As mentioned before, RTC strategies (as an increasingly used tool for urban water pollution remediation) rely on models to optimise the operation of relevant parts of the urban wastewater system. Uncertainties could therefore affect the performance of the RTC strategy, which (if significant enough) should be dealt with or at a minimum accounted for. In the RTC context, large uncertainties exist within the rainfall forecast (when using a real-time optimisation procedure), the system performance (given the potential for failure) and the system state (usually there is only (uncertain) information available at scare points throughout the UDS).

Frameworks to deal with uncertainty in optimisation problems have been set up and can be subdivided into two main groups: (1) robust optimisation and (2) stochastic optimisation (Svensen et al., 2021). The first type relies on a formulation of the worst-case scenario, such that the output solution is optimal for all possible outcomes. In practical terms, this has limited use in the UDS context given the shear uncertainty in rainfall forecast for the urban environment alone (Pedersen, 2021). Using the stochastic method has similar issues in the assumption of some known distribution of the uncertainty associated with weather forecasting, system state and future functioning.

The rapid changing of the urban environment and urban drainage system alike can introduce further uncertainties in both real-time optimisation and heuristic procedures. In the case of the latter, the set points underpinning the strategy might no longer be optimal given the changed system and in the case of the former, the underlying model might no longer represent the system accurately enough. Ensuring optimal operation in a rapidly changing environment could therefore be more difficult than simply finding optimal settings.

Given the context set out in this introduction and the volume of published work on RTC over the past decades, a literature review is first performed to understand the key gaps within the current real-time control literature regarding the performance of such systems with regard to system characteristics and uncertainties. The literature review and the synthesis of the research questions addressed in this thesis are presented in Chapter 2. The review focuses on the performance of real-time control reported in the literature.

2

LITERATURE REVIEW

REAL-TIME Control has been, as mentioned previously, used as a tool to achieve the desired function of UDS since the late 1960s (Borsányi et al., 2008). Since then, various literature reviews examining the state-of-the-art of RTC have been published (Garcìa et al., 2015; Schütze et al., 2004). More recently, Lund et al. (2018) examined the Model Predictive Control (MPC) literature and proposed common terminology to be used. These reviews, however, did not look at the performance potential of the RTC strategies and factors affecting their practical longevity. To understand the potential of RTC over the long term, an understanding of the performance of RTC strategies and factors affecting it needs to be developed. Underlying patterns, beyond current CSO volume emitted (which has been pointed out to be nearly linearly linked to the CSO reduction potential of RTC (Quaranta et al., 2022)). This chapter examines published RTC strategies to assess their performance and influencing factors on their performance, largely based on selected publications and the various details found therein (see Table 2.1).

The scope of this review is set to RTC strategies applied to grey infrastructure in the UDS. Although the implementation of Sustainable Drainage Systems (SuDS) has become more widespread, (Andrés-Doménech et al., 2021; Fletcher et al., 2015) RTC related to specific parts of SuDS (e.g Brasil et al., 2021; Kändler et al., 2019; Lund et al., 2019; Oberascher et al., 2021) are excluded and readers are directed to Xu et al. (2021) for a review of the literature. RTC applied to the wastewater treatment plant (WWTP) as part of the UDS (e.g. van Daal-Rombouts et al., 2017) are considered here given the importance of the interaction between the WWTP and the UDS (Langeveld et al., 2013) and additional control potential due to actuators at the WWTP influencing both UDS and WWTP dynamics (Nielsen et al., 1996).

2.1. FACTORS AFFECTING REAL TIME CONTROL EFFICACY

RTC can be implemented in a variety of ways, which influence the final efficacy and potential of the RTC strategy. The implementation of RTC to UDS can be divided into the overarching strategy, the RTC procedure and the RTC algorithm (Schütze et al., 2004). The RTC strategy refers to the design of the RTC: including the positioning of potentially new actuators, the definition of the objective function and architecture.

This chapter is an adapted version of: van der Werf, J.A., Kapelan, Z. and 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 & Technology*. doi: 10.2166/wst.2022.038

Table 2.1: Overview of the different study details used in this analysis - part(a). N.C. indicate not included calculation

Reference	**Objective**	**Architecture**	**Procedure**	**Max. Potential***
Gelormino and Ricker (1994)	CSO Volume	Centralised	MPC	N.C.
Schilling et al. (1996)	River Impact	Local	Heuristic Rules	50%^
Fuchs et al. (1997)	CSO Volume	Centralised	Heuristic Rules	N.C.
Fuchs et al. (1999)	CSO Volume	Centralised	Fuzzy Logic Rules and rainfall forecast	N.C.
Rauch and Harremoës (1999)	DO Concentration in River	Centralised	MPC	N.C.
Fuchs and Beeneken (2005)	CSO Pollution Load	Centralised	Heuristic Rules	N.C.
Pleau et al. (2005)	CSO Volume	Centralised	Global Optimal Control	N.C.
Langeveld et al. (2013)	River Impact	Local	Heuristic Rules	N.C.
Montestruque and Lemmon (2015)	CSO Volume	Distributed	Various	N.C.
Garofalo et al. (2017)	CSO Volume	Distributed	Gossip-based algorithm	N.C.
Ly et al. (2019)	TSS Emission	Centralised	MPC	N.C.
Kroll et al. (2018b)	CSO Volume	Local	Heuristic Rules	N.C.
Sun et al. (2020b)	CSO Volume	Centralised	MPC	19.7%
Maiolo et al. (2020)	Flooding Volume	Distributed	Heuristic Rules	N.C.
Mounce et al. (2019)	Flooding	Local	Fuzzy Logic Rules	N.C.
Cembellin et al. (2020)	CSO Volume	Distributed	Fuzzy Negotiations	N.C.
Bachmann-Machnik et al. (2021)	TSS Emission	Local	Heuristic Rules	3.2%

** Refers back to the specified objective function*
^ Refers to the potential additional activation of storage in the system

Overview of the different study details used in this analysis - part(b). This table is a continuation of the table on the previous page.

Reference	System Size	# Actuators	Rainfall Data	Reported Reduction*
Gelormino and Ricker (1994)	264,000 m^3**	23	RG 10 Events	26%
Schilling et al. (1996)	80ha	3	RG 5 years	25%^
Fuchs et al. (1997)	56,400 m^3**	3	RG 10 Events	91 %
Fuchs et al. (1999)	7,500 ha	16	13 RGs - 24 Events	37.5%
Rauch and Harremoës (1999)	1,020 ha	5	RG - 1 event	50 %
Fuchs and Beeneken (2005)	260 km^2	Not Specified	25 RGs - 15 events	13.4 %
Pleau et al. (2005)	325 km^2	22	Radar - 2 Years	87 %
Langeveld et al. (2013)	4000 ha	5	RG - 10 years	11-18% ^^
Montestruque and Lemmon (2015)	Not specified	12	RG - 8 years	50 %
Garofalo et al. (2017)	202 ha	91-332	RG - 15 events	23-46 %
Ly et al. (2019)	45.9 ha	4	RG - 31 events	10 %
Kroll et al. (2018b)	251 ha	24	RG - 850 events	60 %
Sun et al. (2020b)	180 ha	6	RG - 10 yrs	13%
Maiolo et al. (2020)	7.6 ha	5-26	RG - 20 events	89-95%
Mounce et al. (2019)	17 ha	1	RG - 3 events	83%
Cembellin et al. (2020)	540 ha	6	RG - 20 days	70 %
Bachmann-Machnik et al. (2021)	109 ha	5	Synth. RG - 30 years	3%

** Refers back to the specified objective function*
***Catchment size not specified, pertains to the storage in the sewer network*
^ Refers to the potential additional activation of storage in the system
^^ Reduction in occurrence of ammonium and dissolved oxygen concentrations exceeding thresholds

The RTC procedure entails the part of the RTC strategy that determines the optimal settings of the actuators in the system. The RTC algorithm refers to the way in which the settings from the RTC procedures are implemented by the actuators. When comparing the efficacy of RTC, this distinction is important.

The following sections discuss the influence of the different factors on the efficacy potential of RTC, based on 17 studies highlighted in the previous page (Table 2.1). These studies were selected to cover the full range in type of RTC and UDS characteristics, as specified in Table 2.1. Other studies might be referenced to reinforce or challenge the lessons learned from the studies in Table 2.1.

2.1.1. PERFORMANCE DEFINITION

The performance of an RTC strategy is its ability to improve the system functioning with respect to the set objective. This can be calculated by either model-based or data-driven methods (van Daal et al., 2017). The former involves running simulations of the system of different rainfall events for the system with and without the RTC rules implemented, the latter compiles datasets before and after the implementation of RTC and ensures they are sufficiently comparable in terms of rainfall characteristics. Both methods are subject to uncertainties arising from model results (Deletic et al., 2012) and monitoring data also being subject to uncertainties (Bertrand-Krajewski et al., 2003).

TYPES OF PERFORMANCES

Here we make the distinction between three forms of performance: Implemented RTC Performance, Theoretical RTC Performance and Maximum Potential Performance (Figure 2.1). The implemented RTC performance refers to real improvement possible for an RTC strategy after implementation. This can only be assessed using data-driven methods, as the uncertainties and common system failures cannot be accurately incorporated into model-based assessments. Using the model-based approach, the theoretical RTC performance can be calculated. This theoretical RTC performance assumes the ideal functioning of the RTC, and can therefore be seen as the upper bound of the practical RTC performance. The maximum potential performance is the absolute upper limit of what could be achieved with any RTC strategy for the studied catchment. Research should clearly indicate which of the performances was assessed.

A significant difference can exist between the theoretical and practical RTC performance, suggesting that results from model-based studies should be treated as an upper limit on the performance (Seggelke et al., 2013). However, the adaptability of RTC after implementation might increase the performance of RTC for unanticipated events in practice, which cannot be included in performance analyses (Pleau et al., 2005). This re-emphasises that practical RTC performance cannot be compared to theoretical RTC performance. Future studies dealing with RTC should explicitly mention which type of performance was assessed, and additional studies aiming to understand the relative difference in performance between these types should be undertaken. In this thesis, theoretical RTC performances are used.

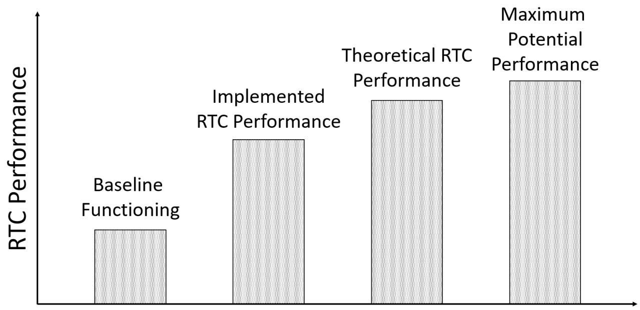

Figure 2.1: Overview of the different types of performances identified

INTER-CATCHMENT PERFORMANCE COMPARISON

One of the hurdles preventing cross-comparing RTC performances in different studies is the lack of a common methodology and reporting on implemented case studies (van Daal et al., 2017). A key inconsistency identified was the difference in the number of rainfall events used for performance evaluations. To get an accurate understanding of the real RTC potential (for both practical and theoretical performance), multiple-year simulation should be done to converge to the real potential, as the performance of an RTC strategy was found to be highly dependent on rainfall characteristics (Tränckner et al., 2007; van Daal et al., 2017). Despite this, longer time periods are not always used (Table 2.1). Another hurdle is the lack of a commonly applied baseline to which the RTC improvement should be compared. Typically, the '*pre-RTC*' functioning of the system is used to show the performance potential; however, it has been shown that using the '*pre-RTC*' functioning as a baseline can lead to large over-estimations of the performance potential due to sub-optimal operation of the system before the RTC was implemented. Reliance on the '*pre-RTC*' baseline can therefore give a skewed understanding of the real benefits of RTC. Statically optimising the system (whereby the baseline is the optimal functioning of the system with a single if-then rule per actuator in the system) as a baseline was proposed (Schütze et al., 2016) and later included in more objective performance indices (see Chapter 4 for this method) developed (Liao et al., 2022; van der Werf et al., 2021); however, these methods are not commonly applied.

Performance assessment on longer time series might not be possible because of a lack of long-term reliable rainfall data, or impractical due to the long computational times necessary for optimisation problems. Extrapolation methods from smaller data sets have been proposed (Meneses et al., 2018), but their underlying assumption of linearity between increased rainfall depth with CSO volume is one that does not hold (Vezzaro, 2022). For the design of optimal RTC, on the other hand, convergence to an optimum can happen faster, within 10 events for the catchment studied by Bachmann-Machnik et al. (2021). However, the size of the catchment and lack of uncertainty analysis contribute to this relatively fast convergence. Using radar data rather than a single rain gauge as an input can necessitate more rainfall data, as the spread of potential rainfall characteristics increases.

2

OTHER PERFORMANCE METRICS

Rather than focussing on the difference between the improvement of the system with RTC compared to before the implementation, other methods to describe the performance of RTC have been proposed. A rating algorithm, akin to the one used for the ranking of chess players, was proposed to describe the relative performance increase of a UDS after RTC implementation (Garbani-Marcantini et al., 2017). Fast convergence using little rainfall data was found using this method. This abstract framing of RTC performance, however, may not be interesting from an operators' perspective and is therefore unlikely to be widely adopted. A metric which combines the descriptive meaning of the current reporting, the objectivity and transferability of the aforementioned method which includes the lack of bias in the assessment (as discussed in the previous section) should be devised.

Despite recent advances in the field, most papers do not explicitly describe how their RTC performs compared to a well-defined baseline nor do they describe that all statistically relevant types of storm events have been captured. This makes comparisons of RTC strategies and procedures from different case studies difficult. As large-scale monitoring systems become more widespread in UDS, direct monitoring of the objective of the RTC strategy (CSO volume, CSO pollutant load, receiving water impact) is key to understanding the implemented performance of RTC systems.

2.1.2. RTC PERFORMANCE POTENTIAL

The RTC potential, or the improvement of the operation of a UDS through RTC regarding the set objective, is not guaranteed to be significant for every catchment while potentially requiring significant investment needs (Beeneken et al., 2013; Campisano et al., 2013; Villeneuve et al., 2000). To give an indication of whether RTC investments are justified, a scoring tool, Planning Aid for Sewer Systems RTC (PASST), was proposed (Schütze et al., 2008). This tool attempts to relate the physical characteristics of a UDS to the performance potential of RTC. Similarly, Zacharof et al. (2004) developed a screening exercise based on the SYNOPSIS tool (Schütze et al., 1999) to assess if a UDS would have sufficient RTC potential to warrant investment. Their application to a single semi-hypothetical UDS suggested that storage volume is the most important property determining RTC potential, a key feature in PASST as well. Nelen (1992) however, showed that for three catchments temporal differences in peak flow (temporal heterogeneity) for parts of the UDS are the key indicator of the RTC potential. Even when the potential for CSO reduction through RTC is low, other objectives can be achieved through RTC (van Daal et al., 2017).

The dependence of RTC potential on the underlying UDS means that the generalisation of control strategies and procedures is difficult. To facilitate implementation, a framework was proposed (Schütze et al., 2008) and later extended to include uncertainty analysis of the models (Breinholt et al., 2008). Investigative studies to see if there is dynamic flexibility in the system are a key part of these frameworks. To identify which pre-existing actuators in a system are of the most interest from a control perspective, a global sensitivity analysis can be performed (Langeveld et al., 2013), a technique later applied to a benchmark case study (Saagi et al., 2016; Saagi et al., 2018) and shown to remain optimal under uncertain model parameters (Ledergerber et al., 2020). This technique also underpins the procedure developed here in Chapter 5. When actuators are added as part of the RTC strategy, locations of interest can be determined through hydrodynamic models (Eulogi et al., 2020; Zhang et al., 2018), by looking for underutilised capacity in the sewer system, independent of the RTC strategy.

Few papers directly quantify the maximum potential performance of RTC for the studied catchment (Table 2.1), although a maximum potential performance for CSO volume was already used in the 1990s(Schilling et al., 1996) and formulated as a 'central-basin approach' (Einfalt & Stölting, 2002). This methodology treats the entire UDS as a single basin, a hypothetical situation in which all the storage in the UDS can be activated, also applied in Bachmann-Machnik et al. (2021) and Schütze et al. (2018). No equivalent methods to the central-basin approach have been formulated for RTC strategies using other objective functions than the reduction of CSO or flooding volume. Using the proposed optimisation function with perfect infinite forecast to approach a more realistic maximum potential of the RTC might fit this role even though it was initially applied to volume-based control only (Fiorelli et al., 2013). Assessment of the total RTC potential should be included in all studies, to gain an objective insight into the real RTC potential and enable improvements to the PASST tool.

The optimisation of the use of existing infrastructure can be a cost-efficient way of ensuring the desired functioning of UDS (Dirckx et al., 2011). A study on the application of RTC to the city of Quebec, Canada, showed a reduction of 83% of total CSO volume (Pleau et al., 2005) and exploratory studies for the city of Flensburg, Germany, show a theoretical reduction of 91% of overflow volumes (Fuchs et al., 1997). Considering the cases of Dresden, Germany, and Vienna, Austria, more modest yet significant theoretical reductions of 37.5 and 13.4% of CSO volume could be reached (Fuchs & Beeneken, 2005; Fuchs et al., 1999). On the other hand, several studies report low efficacies of RTC, some with a CSO volume reduction as low as 0.3% (Bachmann-Machnik et al., 2021), despite indications that RTC might be a useful optimisation tool given the catchment characteristics as outlined in PASST. These discrepancies are a factor that might limit the uptake of RTC in practice, as the significant upfront costs to find out if there is potential for RTC might deter operators from exploring the potential.

A reliable method of estimating the potential *a priori* should be further developed, as more case studies with high-quality data results are now available. Communication of the maximum RTC performance potential is thereby an important part of reporting RTC case studies.

2.1.3. RTC OBJECTIVES

As categorised by Garcìa et al. (2015), the objective of the RTC strategy typically falls under one of three concepts: volume-based, pollution-based and impact-based control (s. Volume-based (VB-RTC) aims to reduce the total CSO or flooding volume and is generally considered the simplest objective function, considering only the hydrodynamics of the UDS system. Pollution-based RTC (PB-RTC) integrates the concentration of pollutants in the system outflows and Impact-based RTC (IB-RTC) additionally considers the effects of these pollutants on the receiving water bodies (thus integrating the receiving water body dynamics within the control strategy). Here PB-RTC, IB-RTC and integrating the WWTP into the objective functions are discussed considering their relative potential benefits and drawbacks compared to VB-RTC.

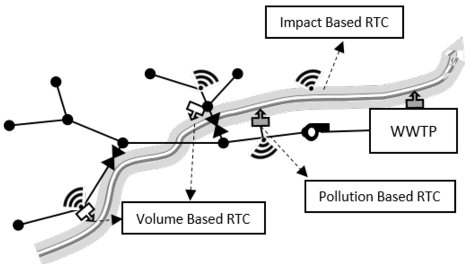

Figure 2.2: Overview of the different types of objectives typically used for the implementation of real-time control

POLLUTION-BASED RTC

The additional potential for pollution reduction through PB-RTC is dependent on the dynamics of the pollutants. Mass-Volume (MV) curves describe the dynamics of pollutants (using total suspended solids as a proxy for total pollution load) and volume of CSOs during an event (Bertrand-Krajewski et al., 1998). Dependent on the shape of the MV-curve, the performance improvement from VB-RTC to PB-RTC changes (Ly et al., 2019). If the start of the event has a relatively higher pollutant concentration than the rest of the event, a decrease in potential was found when compared to relatively higher pollution loads during the middle or late parts of the event. This is in agreement with Lacour and Schütze (2011), who similarly conclude a decrease in PB-RTC potential when a strong first flush effect was added to their highly simplified catchment. First flush phenomena were found to occur scarcely (Saget et al., 1996), consequently improving the theoretical potential of PB-RTC. Catchment-specific dynamics should always be considered and integration of continuous monitoring, such as turbidity measurements as a means of understanding pollution dynamics, is a necessary first step towards PB-RTC (Lacour et al., 2009; Suárez & Puertas, 2005) as long as accurate short-term predictive models cannot deterministically predict these dynamics (Jia et al., 2021; Willems, 2006).

PB-RTC can become a multi-objective optimisation function due to the different relevant pollutants. Lumping together all pollutants into an effluent quality index as a single value for optimisation can solve this issue (Rathnayake & Tanyimboh, 2015). The effects of the formulation of the index, however, were not explicitly investigated, leaving the applicability to real control problems to be further investigated. Reduction of pollutants can also be a direct competition (allowing more stormwater to go to the WWTP might reduce pollution related to CSO events, but can increase the ammonium concentration in the WWTP effluent, (Langeveld et al., 2013)), and using a single index might miss the dynamics which can be explored with different priorities possible.

Impact-based RTC

IB-RTC considers the receiving waterbody's water quality state as the optimisation function, typically focussing on dissolved oxygen (Rauch & Harremoës, 1999) and/or ammonium (Langeveld et al., 2013). From these two parameters, a Pareto front can be generated and operational preferences used to set the optimal strategy (Fu et al., 2008). However, adding a simple cost function to different CSOs due to sensitivity differences in receiving water bodies is a simplified version of IB-RTC (Vezzaro & Grum, 2014), allowing additional overflows in one part of the catchment to relieve another. Using a minimisation objective related to the impact of CSO events might cause additional overflow volume or frequency (Rauch & Harremoës, 1999), which could require legislative changes (Meng et al., 2020), with a similar discussion applying to WWTP emission (Hendriks & Langeveld, 2017).

The non-linear dynamics of solid discharge and the impact of waste discharge make comparing IB-RTC and PB-RTC performance to VB-RTC performance in terms of a simple metric impossible (Rauch & Harremoës, 1996) and methods to attempt this have not been found in the literature. Whether PB-RTC and IB-RTC are more effective than VB-RTC, therefore, remains a largely open question. Methods to appreciate the trade-offs between various pollution loads and their impacts on receiving bodies are necessary to appreciate these benefits but were not found in the literature.

WWTP Integration in RTC Strategies

When considering the impacts of an urban drainage system on the receiving water body, including the dynamics at the WWTP becomes a necessity. IB-RTC in particular should include the WWTP and its dynamics rather than using it as a downstream boundary condition. Here we consider WWTP control affecting the interactions between the WWTP and the drainage system. Process control within the WWTP to optimise activated sludge return, aeration and dosing (e.g. Demey et al., 2001) are not considered here and readers are directed to Newhart et al. (2019) for an overview of data-driven control of these processes.

Reduction of the inflow of the WWTP during wet weather flow (WWF) conditions to avoid ammonium peaks in the WWTP effluent is a viable RTC strategy (van Daal-Rombouts et al., 2017). Flow reduction to the WWTP, however, can cause additional CSO events. This should be weighed against potentially reduced pollutant loading from the WWTP (Hernebring et al., 1998). For the Badalona, Spain, catchment, a rule-based RTC including the inlet pump to the WWTP could reduce the total CSO volume relative to an optimisation-based control system with the WWTP inlet pump as a fixed boundary condition (Romero et al., 2021), showing VB-RTC can also benefit from including the WWTP in the control settings. Similar to the efficacy of the RTC applied to UDS without WWTP consideration, the potential of RTC depends on the WWTP characteristics.

The balance between WWTP intake and CSO events should be regarded from an integrated point of view. This balance can be a key factor, depending on the WWTP capacity, as it could be ecologically beneficial to cause a CSO rather than overload the WWTP (Frehmann et al., 2002). Overflow of the sludge blanket of secondary clarifiers as a result of overloading the WWTP can cause significant ecological damage (Schilling et al., 1996). However, a higher uptake of the WWTP, if designed accordingly, can significantly reduce the total emission load (Seggelke et al., 2005).

Depending on the WWTP configuration, the efficiency of the treatment steps can be sensitive to variations in the influent loading. The variance of the hydraulic, chemical and biological loading to the WWTP can therefore reduce the operational performance of the WWTP (Leitão et al., 2006) A control strategy to mitigate influent variance under dry weather flow (DWF) conditions focussing on pollutant concentrations, changing its objective under WWF conditions, can improve the functioning of the WWTP (Risholt et al., 2002; Troutman et al., 2020). This type of DWF control relies on the attenuation of wastewater in the system during DWF conditions, which can therefore be applied to CSSs with sufficient redundancy. The efficacy of this method should be extended by adding long-term forecasts, to ensure that the system is ready to change from its optimal DWF setting to WWF functioning when rainfall risk is on the horizon.

Novel treatment processes, particularly smaller decentralised units, with more control over the process are being developed (e.g. Piaggio et al. (2022)). Interaction between the in-sewer processes and the treatment capacity could potentially be better exploited in such instances, increasing the potential for integrated RTC procedures to improve UDS-wide operation.

Including the WWTP in the design of the RTC strategy can lead to significant benefits for all types of control. Understanding when there is the most potential, given the UDS and WWTP characteristics remains unknown. The trade-off between pollutants emitted from the system is a key parameter, and factors influencing the optimality of this trade-off should be further considered. A well-considered choice between sectoral (only UDS) and integral (including WWTP) control approaches should be part of the development of RTC, and a methodology to make this decision is missing in the literature.

2.1.4. RTC ARCHITECTURE: PERFORMANCE AND BENEFITS

LOCAL CONTROL

Local control, arguably the simplest form of real-time control procedure, excludes any communication between actuators and relies on the ability of each actuator to optimise its relevant part of the UDS to optimise the system as a whole. Because of this low level of information integration, local control utilises mainly heuristic procedures, thereby relying on an extensive understanding of the system or through prior set point optimisation. This form of control is widely implemented, as even simple *on/off* rules for pump sumps can be argued to fall within this category. *If-then* rules and fuzzy logic rules are the two options available in a local control architecture (Garcìa et al., 2015). Although information integration might be low, it could be argued that there is indirect communication between actuators through the dynamics influenced by the actuators.

The relatively simple, and therefore adjustable nature of local control can make it more appealing for operators compared to centralised control (Mounce et al., 2019), provided that the benefits of the higher-tier architectures are not significant enough. Local control can also lend itself to a more generalised framing of the control strategy, in the form of equal filling degree (whereby the aim is to fill upstream and downstream of a node equally, a strategy sometimes naturally emergent from centralised optimisation-based RTC (Cen & Xi, 2007)) showing reductions ranging from 20–50% of CSO volume for five small catchments in Flanders, Belgium (Table 2.1, Kroll et al. (2018b)). Similar attempts at transference of strategies in-between catchments showed less successful results (Borsányi et al., 2008).

The design of heuristic rules, if done automatically, is dependent on the event characteristics used for the calibration of the rules (Eulogi et al., 2020) and will perform better for events with similar characteristics. A set of rainfall events which are representative of the catchment should be used for rule calibration and multiple years of rain data for the validation of the rules (van Daal et al., 2017).

New methods within the local control architecture are rare, as they are stuck on *if-then* rules and fuzzy logic which are highly case study specific meaning difficult to generalise. New approaches that are better able to utilize digital advances of the last decades are not studied. Methods to allow for the gradual transformation of simple local RTC towards a more complex control system are also not reported, which could help the more widespread adoption of higher-tier RTC systems. A new method to integrate forecasts in a local predictive manner is presented here in Chapter 7.

Centralised Control

In a centralised control structure, all the information relevant to the RTC procedure is received by a central agent, which computes the optimal settings for all actuators and returns those to be implemented. The central agent determines the set points either through a heuristic procedure or using real-time optimisation, for example through MPC. This form of RTC is regularly shown to outperform other forms of RTC (Gelormino & Ricker, 1994; Giraldo et al., 2010), although the margins are not always significant (Sun et al. 2020a) and other architectures can similarly optimise the system (Table 2.1). Verification of the potential of this type of RTC for a given catchment is therefore more important prior to making the necessary investments.

A centralised control structure does not have to be automated. Catchments can rely on local control, with the flexibility of being overruled from a central control location if desired by operators. This application leads to a 50 and 10% reduction in CSO frequency and volume respectively, based on operational data (Weyand, 2002). Verification of these forms of RTC compared to other control options, however, are impossible given the ad-hoc nature of manual control. Increased costs for personnel might also be problematic and an increase in this has been set as a hard constraint for other projects (Pleau et al., 2005).

The reliance on extensive wireless telecommunication networks is a potential drawback for centralised control systems. Any RTC strategy should have built-in contingencies to ensure resilience against information loss. Integration of data-filling techniques using artificial intelligence to supplement missing data or validate real-time data has been shown to be promising (Palmitessa et al., 2021). Application of these techniques could enhance the resilience of RTC to likely incidents of data loss, one of the major faults previously found to occur (Weyand, 2002) and accounted for in more recent applications (Seggelke et al., 2013). This resilience should go beyond returning to a passive or local control strategy.

The largest potential for centralised control seems to come from larger, complicated UDS with a high (> 5) number of actuators (Table 2.1). The layout of such larger systems ensures that complicated dynamics emerge, which are more difficult to optimally control with a local control strategy, especially when a high level of control is present due to the number of actuators. Additional benefits of the predictive nature of MPC can arise, especially in a large catchment where the spatial heterogeneity of the inflow can be anticipated and accounted for in the control procedure.

The arising abundance of cheaper options for monitoring networks and the legal necessity to accurately report on CSO discharges means that information flows for sewer systems are being established, regardless of RTC implementation. With this plethora of newly available information and telecommunication structures in place (Montserrat et al., 2015), one of the main hurdles for the implementation of more complex centralised control strategies is decreasing. This is combined with increasing computing power and optimisation algorithms, able to handle more complex optimisation problems.

Although centralised control architectures have been widely studied, it remains unclear when centralised control can outperform other architectures significantly enough to warrant the additional investments needed. Worsening of the performance due to invalid underlying assumptions can also happen in practice and ensuring this does not happen should be an integral part of centralised RTC.

DISTRIBUTED CONTROL

Utilising the relatively small tele-communicative footprint of local control, distributed control incorporates communication between actuators, rather than a central controlling agent as per centralised control. Subsections of actuators find the best solution for each actuator, through Nash-equilibria, gossip-based algorithms (Garofalo et al., 2017) or through heuristic rules (Alex et al., 2008). Similarly, Ramirez-Jaime et al. (2016) achieve comparable results between a distributed control system and a centralised MPC scheme for a small catchment without the relative complexities associated with MPC, a point reiterated for water distribution networks by Barreiro-Gomez et al. (2017). Furthermore, they find improved fault-tolerant properties to information loss in the distributed architecture compared to centralised control architectures, resulting in a higher performance of the RTC strategies under realistic operating conditions.

The virtual catchments studied have a high level of controllability over the dynamics in the system, with the percentage of conduits able to control the flow rate passed through them being 26%, 28–99% and 19–100% by Ramirez-Jaime et al. (2016). Garofalo et al. (2017) and Maiolo et al. (2020) respectively (Table 2.1). This density of actuators is far higher than can be reasonably expected in real systems, which will likely lead to an underestimation of the difference with a centralised control approach. A distributed RTC was implemented in South Bend, US (Montestruque & Lemmon, 2015; Wan & Lemmon, 2007), where the discharge rate into the main interceptor from trunk lines in the UDS was set based on various control algorithms. Simulations predict a potential 25% reduction in CSO volume, but operational data indicated a reduction closer to 50%. This large discrepancy can, in part, be attributed to inter-annual variation in rainfall characteristics and model uncertainty. Changes to the system during operation, however, were not considered in the simulation, which likely contributed significantly to the difference between the simulated and observed RTC potential, highlighting the potential impact changes to the system can have on the performance of a UDS. From this data, it is therefore impossible to attribute the monitored system efficacy to the RTC alone (although a 12% mass balance error was reported), despite the application of RTC reducing the cost of the CSO mitigation plan by around $150 million.

A standardisation of the distributed control design was proposed and close proximity to the theoretical maximum performance was achievable (48% CSO volume reduction, Alex et al. (2008)). The oversimplified system on which this was tested, however, meant that the extrapolation to other systems is unlikely to yield the same result. Implementation of the standardised procedure in other catchments has not yet been reported in the literature.

The addition of actuators in the context of distributed control can also lead to negative outcomes: increased risk of flooding (Ramirez-Jaime et al., 2016) or decreased flooding volume reduction (Maiolo et al., 2020). The latter claimed flooding volume reductions for a UDS without CSO structure of 89% and 62% for a partially and fully controlled small drainage system respectively for a 1-in-20-year storm compared to a UDS with only unrestricted flow. Some inconsistencies in mass balance through conduits seem to arise, which was not explored further in the study. Using fewer actuators also showed a higher potential, which is left unexplained, but likely due to sub-optimalities in the RTC procedure. A coordinating, centralised control might have avoided decreases in efficacy, as the overarching layer uses the state of the entire system to activate the appropriate storage.

The potential of distributed control could increase with the expansion of low-power wide-area networks (LoRaWAN). Wireless telecommunication networks are cheap and can be paired with cheap, low-battery powered sensors, but suffer from a relatively small transmission range and high data loss through signal suppression and interference. However, it can be used to monitor in-sewer processes (Ebi et al., 2019; Gineprini et al., 2020) and application to industrial control systems is being tested (Hoang et al., 2020). This combined with recent advances in cheap sensor (Shi et al., 2021) can lead to an increased potential of decentralised control.

The potential of distributed control has been shown in theoretical case studies, but their implementation into real case studies remains limited. Understanding of the true difference in potential with centralised control can therefore not yet be asserted.

ARCHITECTURE DISCUSSION

All previously discussed control architectures have their merit and should be applied in different contexts. Centralised control enables the highest efficacy with respect to CSO and flooding reduction. However, their relatively high cost can be a major hurdle for implementation. For small and simple UDS, local control generally performs as well as centralised control, and should therefore be seen as either the best solution or an initial step towards optimal control.

Distributed control appears to be particularly useful when the density of actuators is high, or when the controlled sections discharge into a single transport conduit. Its fault-tolerant properties, however, might ensure that the long-term performance is better compared to centralised control if faults have not been explicitly integrated into the centralised strategy and occur frequently. The right architecture, therefore, depends on the preferences of the operator. Centralised control, however, has more options in terms of utilising forecasts and improvement in computing power. Additional models and insights are also relatively easy to integrate in a centralised control architecture but are not exclusive. A systematic assessment of the benefits of the different architectures for different catchments with a wide variety of properties in terms of size, actuator numbers and loading should be undertaken. Limiting to a single catchment for benchmarking, such as the Astlingen case study (Schütze et al., 2018) should be replaced with a set of catchments (Lund et al., 2018), as the benefits of the different architectures are highly dependent on the UDS.

2.1.5. RTC PROCEDURES

The procedures of RTC, the way in which the system determines the set points for the actuators (Schütze et al., 2004), can be divided into heuristic and optimisation-based control (Garcìa et al., 2015). Heuristics are based on extensive knowledge of the system (through the set point of actuators, or fuzzy logic-based control) and optimisation-based control computes the best settings for the actuators at every specified time interval based on a model of the system (See Figure 2.3. Heuristic control procedures are widely adopted in practice due to their relative simplicity and intuitive way of working, although significant efforts (modelling and monitoring campaigns) can still be required.

HEURISTIC CONTROL

As previously mentioned. a benchmarking case study, to test different procedures in terms of computational speed and efficiency, has been proposed (Schütze et al., 2018) and is freely available. However, the catchment is highly simplified, meaning the step of simplifying the system to a control-orientated model (Garcìa et al., 2015) is not part of the benchmarking section. This simplification step is a key part of the development of an RTC strategy and procedure, thus using a simplified catchment as a benchmark, therefore, does not do justice to the complexity of RTC. Furthermore, using a single catchment as a benchmark will likely limit potential insights to be gained. Using several catchments with different characteristics as a benchmarking set should therefore be encouraged (Lund et al., 2018). More datasets and models, similar to Pedersen et al. (2021b), should be made available.

In various studies, heuristic control underperforms compared to optimisation-based control regarding the objective function (Mollerup et al., 2016) although the difference

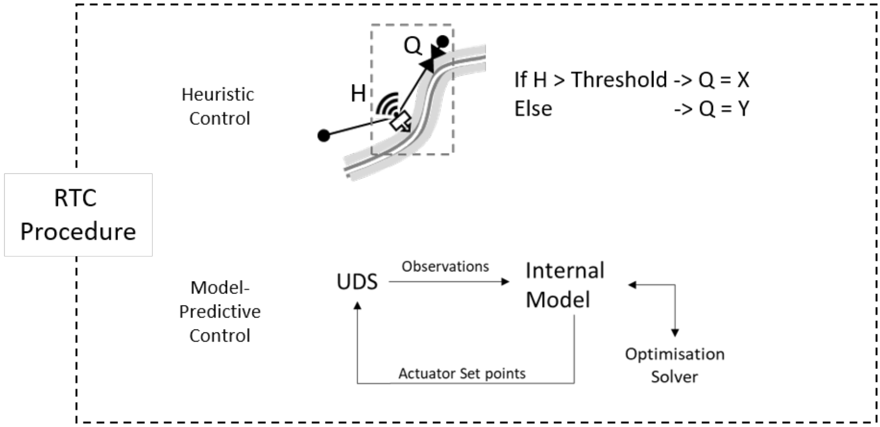

Figure 2.3: Graphical representation of the two main control procedures considered: Heuristic and Model-Predictive Control

in efficacy can be too little to warrant the additional expenditure required (Mollerup et al., 2017; Mollerup et al., 2015). The generalisation of relatively simple heuristic rules for application in different catchments can be possible if the catchment variation is limited (Kroll et al., 2018b). These generalisations, based on the '*equal filling degree*' principle (ensuring that the catchment aims to minimise the difference in filling degree between various parts), can ensure further uptake of heuristic control in currently uncontrolled UDS.

Short-term rainfall forecasts (nowcasting) can be integrated into heuristic control (Fuchs et al., 1999). Studies to investigate the added potential of nowcasting in heuristic control, however, were not found. Furthermore, the influence of nowcasting uncertainty on the control potential has not been investigated (See Chapter 7).

MODEL PREDICTIVE CONTROL

The benefits of real-time optimisation-based control appear to arise in more dynamic and heterogeneous systems, whereby multiple actuators influence the sections in different proportions (Table 2.1). Indeed, the relatively small benefits of optimisation-based control mentioned earlier applied to small catchments, whereas real-time optimisation-based control showed greater benefits over heuristic control for the large system of Quebec (Pleau et al., 2005). The size of the catchment alone, however, cannot be used as a proxy for potential, as also acknowledged in the PASST tool.

Model-predictive control (MPC) relies on nowcasting and an optimisation model to determine the optimal settings for the actuators. Numerical nowcasting, however, remains a large source of uncertainty and can contribute to efficacy loss when real radar forecasts are used (Krämer et al., 2007; Löwe et al., 2016) compared to perfect forecasts (Vezzaro & Grum, 2014). The effect of the uncertainty within the nowcast is reduced due to the updating of the initial conditions for every time-step (Fiorelli et al., 2013) and the discount factor in the optimisation function places less emphasis on the further horizon values. Accurate estimations of the initial conditions are therefore key to a successful implementation of MPC. Furthermore, the theoretically limited impact of inaccurate rainfall prediction on the performance of control strategies was shown earlier (Nelen, 1992; Trotta et al., 1977). Given this, the actual added benefit of nowcasting in RTC compared to other real-time optimisation methods remains the question. Chapter 6 goes deeper into the details of forecast-related errors and their impact on RTC efficacy.

The influence of the uncertainty of the updated initial conditions in the internal-MPC model has not been accounted for in the literature. Especially the runoff module in the optimisation model requires information not normally included in the MPC procedure (e.g. infiltration parameters) and can thereby lead to uncertainty about the future states. Some researchers use a full-hydrodynamic model to estimate the state at every time interval (Cembrano, 2004; Joseph-Duran et al., 2014), however, the assumption that this can reflect the real initial condition adequately has not been tested.

To deal with this uncertainty in the rainfall forecast in the MPC context, chance-constrained stochastic optimisation (Svensen et al., 2021) and risk-based optimisation (Courdent et al., 2015) have been proposed. Both formulate the inflows as a probabilistic value rather than deterministic and search for an optimum for all situations within given bounds. Courdent et al. (2015) uses the ensemble of rainfall predictions to determine the risk of settings with respect to weighted CSO volumes. This is a realistic and more reliable way as it uses the real way in which nowcast data can be available to operators

Critically, when assessing the influence of nowcast uncertainty, the full dynamics of forecast uncertainty should be acknowledged: spatial, temporal and magnitudinal. Adding a normal distribution to the rainfall intensity, as is the case in the aforementioned papers (with the exception of Courdent et al. (2015)), cannot accurately represent all uncertainties. Investigation of the full range of nowcast uncertainties and their effect on the optimisation outcomes remains an important open question in the literature.

Most papers considering forecasting use a relatively small horizon (typically of 2 hours) as this type of data is often available in a commercial setting. The influence of the nowcast horizon on the potential of RTC depends on the characteristics of the UDS and the RTC strategy used. The RTC potential was found to level off after 1.5 hours for a conceptual catchment (Rauch & Harremoës, 1999), which was unsurprising given its small size. The optimisation potential of using forecasts described by Nelen (1992) follows a similar pattern. It should be noted, however, that the potential for long-term forecasts (> 12hours) through numerical weather prediction was not considered in these papers. These forecasts can contribute to the safe and optimal emptying of larger UDS or solids settling tanks (SSTs).

The lack of adoption in practice of MPC can also be attributed to the more complicated nature of the control set-up. The availability of pre-made MPC algorithms for EPA SWMM (Sadler et al., 2019) and other open-source software packages (Bartos & Kerkez, 2021; Mason et al., 2021; Rimer et al., 2021) can benefit the implementation of optimisation-based control. It allows operators to have a low entry-level point to MPC, with tweaking possibilities available in the open-source nature of the code. Selection of the optimisation algorithm, given the plethora of different algorithms, is less important (Jahandideh-Tehrani et al., 2021).

The real benefits of optimisation-based over heuristics are highly dependent on the UDS characteristics, though factors influencing this have not been studied explicitly. Specific attention to the uncertainties in optimisation-based algorithms should always be included to ensure that the optimal settings computed are sufficiently reflective of the system. Risk-based approaches are promising, although their application in real systems has not been reported. Case studies with data on optimisation-based functioning should be encouraged to be published to gain better insights into the RTC potential.

2.1.6. RTC RELATED RISKS

Despite the benefits of RTC, as set out in the previous chapters, consideration of the risks that are associated with RTC should always be explicitly considered. The main risks emerge from information failure, actuator failure, forecast error (see Section 2.1.4), system behaviour and malicious attacks. The inclusion of fault diagnosis to respond to potential failures can therefore improve the system. Puig (2010) showed a set-membership approach to redefine the constraints set on the optimisation function, able to mitigate additional damage from actuator failings. The diagnosis of faults remains problematic due to inherently large uncertainties in the model and sensor outputs.

In the case of flow restrictive devices, it should be ensured that there is no failure mechanism that can completely close the actuator in case of a failure mode. Such failures can lead to increased spills and flooding, even during DWF conditions. There have been no reports of these forms of failures, but they remain a potential threat. Through deliberate retention of water in the system to avoid CSO events, the risk of flooding could increase (Garofalo et al., 2017). This flood risk can increase with the addition of more actuators, compensated by a decrease in CSO volume. Integration of this additional flood risk is an important part of the design of the RTC strategy. This risk might be exacerbated if changes in the system are not propagated into the RTC procedure.

Increased automation and information streams can make the UDS more vulnerable to cybersecurity incidents. WWTPs have been subject to such incidents with the discharge of untreated wastewater as a result (Hassanzadeh et al., 2020). Actuators in the UDS, especially in the case of centralised control architecture, could become vulnerable to cybersecurity threats. This is not to say that local control is immune to malicious attacks, as most manholes are easily accessible. Previously proven security measures should therefore always be an integral part of the application of RTC to real catchments.

Continued monitoring of the RTC performance can help in the mitigation of the risk, through early detection of malicious actors and sensor failure. Additional redundancy in the monitoring network (by adding multiple sensors at the same location) might mitigate against some forms of sensor failure, but will simultaneously increase the overall RTC costs. Methodologies to ensure risk mitigation, however, are limited to fault tolerance in sensor and actuator performance. From the literature, it appears that this alone is not enough to ensure the long-term enhanced performance of RTC.

2.2. UDS CHANGES AND THEIR POTENTIAL EFFECT ON RTC EFFICACY

The interaction between RTC and the sewer system happens on different timescales (Mollerup et al., 2017). However, over the longer timescales, the UDS will have undergone changes influencing the behaviour of the system. These changes can have an impact on the overall performance of the RTC strategy, and given that lack of cooperation between planning and operation departments has been highlighted as an impediment to RTC adoption (Lund et al., 2018), understanding how these changes affect the RTC performance can become an important step towards more ubiquitous adoption of more advance RTC procedures. Datasets such as those presented by Pedersen et al. (2021b) are an important tool in understanding the long-term performance of RTC, and they should ensure that the documentation of changes to the system is mapped out in such datasets (van Daal et al., 2017). Here, we review the literature on what changes can be expected to happen to the UDS over the short- and long-term and relate them to the performance potential of RTC. Gaps in knowledge are identified and expanded on.

Changes to the system can be divided into four main types: Contextual changes, large-impact configurational changes, small-impact configurational changes and temporary operational changes (Table 2.2). Their relative impacts on the UDS and thereby the RTC performance potential are discussed below.

Table 2.2: Different types of UDS changes considered, detailing the description and examples of the types of changes defined here

Type of Change	**Description**	**Examples**
Contextual changes	Non-physical changes which have an impact on the UDS	Requirements set for UDS change; change in prevailing climate
Large-impact configurational change	Permanent physical changes to the UDS which significantly impact the objective function of an RTC strategy	Installation of a new storage tank; expansion of pumping capacity
Small-impact configurational change	Permanent physical changes to the UDS don't significantly impact the objective function on their own.	Local implementation of SUDS; relining of conduits; local densification
Temporary operational change	Temporary change in the operational capacity of the system	Pumping capacity loss; data transmission loss; actuator failure

2.2.1. CONTEXTUAL CHANGES

LEGISLATION

The reduction of pollutants through the UDS is driven by increasingly stringent legislation. In the EU, the original Urban Waste Water Treatment Directive of 1991 (Council Directive 91/271/EEC), specified the treatment targets and is being revised at the moment of writing to include more stringent requirements to the UDS and the Water Framework Directive (WFD) of 2000 (Council Directive 2000/60/EC) the targets for a good ecological, chemical and physical state of the natural water bodies. The WFD marks a trend towards an impact-based approach to water policy although enforcement remains questionable (Kallis, 2001). A new Urban Waste Water Treatment Directive is currently under public consultation, and is likely to include an additional target for micro-pollutants emitted from UDS and more restrictions on the emission of untreated wastewater, arising from findings based on uncalibrated models that the current targets are not being met consistently in all member states (Pistocchi et al., 2019). An increased call for optimisation of the existing infrastructure is also specified within the new UWWTD, putting RTC further on the forefront in the search for a sustainable form of wastewater management.

Legislation is bound to influence the objective functions set for the RTC strategy, influencing the performance potential. Some RTC procedures have been found to increase the frequency of CSO events whilst decreasing the overall volume (Cembellin et al., 2020). RTC as the basis for environmental permitting could be a flexible and efficient way to implement legislation (Meng et al., 2020).

Legal requirements might also arise to reduce greenhouse gas (GHG) emissions from the urban water cycle. GHG emissions occur along the UDS, through the power demand of pumps in the sewer system, to in-sewer processes generating GHGs. Mechanisms to include the estimation of GHG emissions in the formulation of UDS control strategies have been developed (Flores-Alsina et al., 2011) and a control strategy specifically to minimise the energy consumption of the entire UDS without additional pollution was developed, noting that catchment-wide energy saving can only be done through investigation of both up-and downstream indicators (Kroll et al., 2018a). Co-optimisation of both CSO reduction and energy consumption was shown as promising for control (Bonamente et al., 2020), although the conceptual UDS used has little basis in reality. Despite this new emphasis on GHG emissions in UDS control strategies, the specific focus on climate and social sustainability of RTC for UDS is still in its early stages (Ashagre et al., 2020). Heat recovery from the UDS (Nagpal et al., 2021) might also add new demands to the functioning of the system, which could influence operator preferences and therefore RTC functionality.

Operational cost reductions due to a fluctuating abundance of renewable energy can be incorporated into an MPC system for WWTP (Ostojin et al., 2011; Stentoft et al., 2020). This mainly entailed pumping when energy prices were low. Uncertainties should be explicitly considered in these systems, however, as inaccurate model parameters, precipitation forecast and real-time data could cause additional overflows and reduce effluent quality. Furthermore, the purposeful storing of wastewater in a sewer, thereby increasing the hydraulic retention time, can lead to increase GHG emissions from the sewer (Kyung et al., 2017), increase in biofilm production (and thereby more GHG emission potential) and sewer-pipe corrosion (Jensen et al., 2016). Attempting to reduce GHG from the urban wastewater system should include estimations of in-sewer processes, although for accurate model results more research into the physical processes underpinning the emissions is necessary (Mannina et al., 2018).

Resource recovery from WWTPs (thereby becoming water resource recovery facilities (WRRFs)) is becoming more ubiquitous (Solon et al., 2019; van der Hoek et al., 2016). Resource recovery can benefit largely from a stable inflow of chemical content (Nowak et al. 2015), which has already been shown to be a possible RTC objective (Troutman et al. 2020). As the recovery of resources becomes a more important part of the WWTPs/WRRFs, this type of control is likely to become more prominently used in practice, providing the associated risks (see section 2.6) can be minimised. Using new data sources, like smart meters of water consumption, can generate a more detailed picture of the DWF in a system (Lund et al. 2021; Zhang et al. 2021), opening new possibilities for DWF based RTC. Research in the potential of integrating this new data source has not been reported. Additionally, the performance evaluation of WWRFs might be more complex (Bhambhani et al., 2022), meaning that robust objective functions should be established.

The legislative drive to reduce both GHG emissions and increase treatment of micropollutants are competing goals as the required treatment steps will be energy intensive (Jones et al., 2007). Adding additional treatment steps to the WWTP will also increase treatment cost, which can become problematic as the affordability of access to sanitation needs to be ensured following the United Nations Sustainability Development Goals. RTC's ability to ensure the minimisation of both the economic and carbon footprint of tertiary and quaternary treatment steps as well as resource recovery systems from an integrated WWTP and UDS point of view is unknown and remains an important research direction. All these additional aims are relevant to the urban wastewater systems are included in the new (conceptual) version of the UWWTD.

Climate Change

Anthropogenic climate change is projected to alter the rainfall patterns over the coming decades, although the climate models are difficult to downscale to a small time- and space-scale needed for UDS modelling, meaning the assessment of hydrological impacts remains problematic (Willems et al., 2012). Results of downscaling are also found to be non-transferable, meaning in some catchments climate extremes with regard to rainfall might be exacerbated. For Flanders and the Netherlands, a standardised time-series tool was developed to aid in decision-making concerning climate-adaptive cities (Bakker & Bessembinder, 2012). As CSO should only occur when the full UDS capacity is reached, a non-linear increase in CSO volume under different climate scenarios due to increased rainfall intensity is expected and has been reported for cities in Norway and Canada (Gooré Bi et al., 2015; Nie et al., 2009; Nilsen et al., 2011).

The implication of increased rainfall intensity on the functioning of a heuristic VB-RTC system showed a decrease in a relative reduction of CSO volume by the RTC for a catchment in Flanders (Dirckx et al., 2017). The implementation of RTC was considered a 'no-regret' measure, however, as it still managed to reduce the total overflow volume. Using a PB-RTC or IB-RTC strategy instead might become more interesting, as changes in concentrations might be controlled, even when volumetric capacity is reached (Sun et al., 2020c). This was concluded after only simulating four rainfall events, therefore the validity of this conclusion needs further investigation. In-river dynamics might significantly alter due to temperatures, and these should be considered in the control rules especially if a switch to nutrient control as WWTP effluent standard (as recommended by Hendriks and Langeveld (2017)) is made. Assessment of potential divergence of optimal rules given increased temperature for IB-RTC has not been performed and should be prioritised.

The larger effect of climate change, however, will not be increased frequency of intense rainfall events, but rather the changes that will be made to the urban environment and UDS to mitigate these effects (Kourtis & Tsihrintzis, 2021). When the awareness of water issues inevitably results in the widespread adoption of what is known in China as 'Sponge Cities' (Jiang et al., 2018), RTC of combined sewer systems is unlikely to remain a major factor in CSO pollution reduction. In Chapter 8, the impact of such long-term transitions is further examined.

Although the RTC and UDS literature as a whole has investigated the potential impacts of physical effects of climate change (increased rainfall intensity and higher temperatures), there is no research on the impacts of greener cities on the performance of RTC. To ensure that RTC truly is a 'no-regret' solution to CSOs, further research into this area is necessary.

2.2.2. CONFIGURATIONAL CHANGES

Transitional modelling attempts to identify pathways which can occur for a given UDS (Zischg et al., 2019), but long-term changes are always subject to deep uncertainty making prediction and long-term planning challenging (Babovic et al., 2018). Changes in the system will affect the efficacy of RTC and might require an overhaul of the implemented strategy or procedure depending on the effects. Here we discuss likely changes that can occur to a UDS and examine the potential impacts they might have on the functioning of an RTC strategy.

GREEN-BLUE-GREY SOLUTIONS

To ensure legal compliance and reduce ecological and economic damages from heavy loading or overloading the UDS, green-blue-grey solutions are often implemented. These measures are specifically designed to reduce urban flooding or pollution and should therefore have an effect on the flow rates throughout the UDS, potentially affecting the optimal settings in the case of a heuristic RTC strategy and the validity of the internal MPC model in the case of an optimisation-based RTC strategy. These changes include both small-impact and large-impact configuration changes (Table 2.2).

The optimisation of the rehabilitation of sewer networks can reduce construction costs of grey solutions if the effective gains cannot be achieved through RTC (Vojinovic et al. 2014; Baek et al. 2015). Optimisation of green-blue-grey (GBG) solutions for urban flooding can give insights into the multiple benefits and co-benefits within each solution (Alves et al., 2020). The quantification of co-benefits for green-blue (GB) solutions in particular remains a central issue to the optimisation of their implementation.

Considering GB solutions, the spatial distribution and type of solution are a key influence on their potential for CSO reduction, but the location of CSO structures is equally important (Joshi et al., 2021). GB solutions rely mainly on the (temporal) attenuation of urban runoff, thereby either flattening the peak load to the sewer or reducing the runoff altogether (Fletcher et al., 2015). This would be a beneficial change to the UDS for RTC performance, as the runoff response of larger storm events decreases in intensity, and falls within the range in which RTC is most effective (Vezzaro, 2022). This is not explicitly investigated and cannot be generalised, as the relative potential of RTC has been reported to decrease with the implementation of GB solutions (Altobelli et al., 2020). If GB solutions become so prevalent that all urban runoff is completely infiltrated, RTC can remain relevant by shifting its focus to the application within GB solutions (Xu et al., 2021). The stability of the WWTP inflow and pollution dynamics also becomes more dominant.

If heuristic rules have been used to set up the RTC procedure, and significant investments are made into GB solutions, the re-evaluation of the rules will have to happen. The shift in the system loading, especially when the changes are spatially heterogeneous, can cause the rules not only to be sub-optimal but possibly exacerbate CSO events. The development of methodologies that provide a robust way of assessing the continued functionality of RTC strategy under model uncertainty should become a research priority to ensure the long-term functioning of the RTC strategies. An MPC procedure will also need frequent updates of the underlying model to ensure that the automated procedures remain optimal. Adjustment of the underlying detailed model (digital twin) should be relatively straightforward (although there are still significant gains to be made here (Pedersen et al., 2021a), and emphasis on new data-assimilation techniques (e.g. Milašinović et al. (2022)) in literature studies should be encouraged), though the control-oriented model might be more difficult given the number of data point necessary for simplification (e.g. Garzón et al. (2022) and Mahmoodian et al. (2018)), thus raising the overall cost of maintenance. Understanding RTC efficacy can decrease over time and the trade-off between model maintenance and RTC performance is a key factor in ensuring the longevity of RTC strategies.

To ensure the optimal functioning of the UDS, consideration should be taken to the existing RTC during the planning phase of the GB solutions to ensure that the optimal effects of the GB solutions are achieved, as was previously shown to be important for grey infrastructure implementations in controlled catchments (Fradet et al., 2011). Integration of the co-benefits of GB solutions could prove too reliant on operational preferences to formalise for inter-catchment use. Integrated modelling of the entire UDS, including receiving water bodies, should be considered for the optimised rehabilitation as it gives a better insight into the impact of measures on all the relevant facets (Benedetti et al., 2013b). Explicit research into formal optimisation of these directions has not been reported but should become an important research direction as both GB solutions and RTC become more widely adopted in urban areas.

Grey solutions (implementation of stormwater settling tanks, creation of separate sewer systems, enlarging the drainage pipes and increasing pump capacity) will have a more profound effect on the hydraulics within the UDS itself rather than the inflow amount. In combination with actuator addition, this could lead to more latent storage. Indeed, Altobelli et al. (2020) reported a relative increase in RTC efficacy with the implementation of SSTs in their hydrodynamic model, improving the CSO volume reduction from 34 to 41% compared to their statically controlled counterparts, with the investigated sizes of possible tanks not playing a significant role in this. From this, a co-optimisation of UDS rehabilitation (as presented in Vojinovic et al. (2014) and RTC could prove an interesting area of research, although the double optimisation function might become too computationally expensive. Release of retained water by SSTs in the system can increase the removal efficacy of the suspended solids, particularly the smaller fraction (Muschalla et al., 2014), making the potential for PB-RTC in UDS a more interesting option. The addition of grey infrastructure can lead to new dynamics in the system, which can be exploited through RTC.

2

The above statements are particularly relevant to retrofitted RTC strategies: strategies applied to pre-existing UDS. Although the relevance of this type of RTC might decrease due to the UDS changes outlined before, rapid urbanisation in developing countries where UDS have to be designed can take full advantage of the benefits of RTC within the design phase. Attention in literature should therefore go not only to the optimisation of the design of sewer systems, or RTC optimisation of existing infrastructure but to the dual optimisation of design and operation. Methodologies to automate the generation of fast models necessary for RTC development can play a major role in this and have been proposed (Kroll et al., 2017) but should be tested further and expanded upon to ensure their validity.

Actuators Addition

Several studies do investigate the potential of RTC in combination with the addition of actuators, or increasing the static or pumping capacity as part of the RTC strategy. The attribution of the performance to the real-time procedure of the strategy is not always separately investigated. Cembrano (2004) added a reservoir to the Barcelona case study in conjunction with an RTC system. The RTC strategy was able to improve the system performance but in a very limited way ($<1\%$ for total CSO volume). Interestingly, the RTC worked better for heavy rain episodes to alleviate flooding (5% decrease in flooding volume, $9000m^3$ vs. $6000m^3$ for CSO volume), due to the location of the installed reservoir, showing the effect of the location of actuators on the RTC procedure potential. With a second tank installed, the MPC system could achieve a 17% total CSO volume reduction for small events compared to a static reservoir, and 28% reduction of flooding volume for larger upstream events (Ocampo-Martinez et al., 2013; Puig et al., 2009).

Optimisation of the location and number of actuators is a key part in an RTC strategy that includes actuator placement. In larger UDS, this problem can become computationally too expensive if all manholes (or nodes in a model context) can be considered as a potential actuator location (Leitão et al., 2018). For VB-RTC, the in-sewer storage potential can be calculated to determine the optimal positioning of flow control devices, allowing a reduction in complexity of the optimisation problem (Eulogi et al., 2020).

Full package options (actuators, relevant software and hardware) are becoming commercially available (e.g. CENTAUR project, Shepherd et al. (2016), which might lead to more widespread adoption of RTC. Co-optimisation of added actuators and other GBG solutions has not been investigated. The potential of this co-optimisation should be studied in relation to other changes outlined above

2.2.3. TEMPORARY OPERATIONAL CHANGES

Short-term changes frequently occur in UDS. Pump failure, pump capacity loss, maintenance works and WWTP capacity reduction unavoidably happen and have an impact on the UDS. Failure events have been found to be responsible for a significant number of CSO events (Korving & Clemens, 2005) although overlooked in a recent review of factors. affecting sewer overflows (Mohandes et al., 2022). If a system is re-balanced through RTC procedures, the impact of decreased pumping capacity could lead to worse performance of the UDS compared to a baseline. Similar observations were made for integrated control, with different defects in the WWTP showing lower robustness of the control strategies compared to the status-quo control (Vanrolleghem et al., 2005). Assumptions that the control actions can be carried out by actuators and downstream pumps as a non-variate boundary condition, therefore, do not hold, and the impact of such assumptions should be studied in the context of the different control architectures. These impacts will be more pronounced in systems reliant on pumps for the conveyance of water. The impact of pump failure on the performance of MPC and RTC is further highlighted in Section 4.1.5 and Chapter 6.

Explicit encoding of operational variables that can be considered by optimisation functions could therefore be an important factor in ensuring the resilience of RTC strategy, though the impacts and solutions have not been given attention in the literature. Using data-driven models or deep reinforcement learning agents (e.g. Darsono and Labadie (2007)) can be particularly vulnerable to these temporary changes if not used in the training data, with decreased efficacy, as a result, (Saliba et al., 2020). The black-box nature of reinforcement agents can make it harder for posterior analysis of why decisions were made and the addition of safety control can be harder (Bowes et al., 2020). Methods should be developed to consider these factors in data-driven techniques as well.

2.3. SUMMARY OF KEY GAPS

Despite the scientific maturity of RTC applied to UDS, the long-term functioning of these systems has not been given sufficient attention in the scientific literature. This is likely to be one of the contributing factors to the lack of adoption of RTC in practice. Based on the review, we highlight three main areas in the literature where gaps in the knowledge are most pressing:

- **Objective Performance Potential**. A precise and unbiased definition of the performance of an RTC system, in terms of the baseline and rainfall events necessary, is still to be provided. For this reason, inter-catchment studies to understand the

RTC performance potential and the ability to understand what characteristics of UDS influence the RTC potential remain unknown;

- **Influence of Uncertainty**. Models and monitoring data are both notoriously subject to uncertainties within the UDS context. Both are poised to influence the efficacy of RTC systems and the interactions should be better understood. Although some research was found on the influence of rainfall nowcast uncertainty on the performance of RTC, this is a limited source of uncertainty within the RTC procedure. A better understanding of the influence of all sources of uncertainty, pertaining to both heuristic and real-time optimisation procedures, should be developed;

- **Adaptability of RTC systems to uncertain future changes**. The continuous functioning of RTC systems over longer time periods, whereby significant changes occur to both the urban drainage system itself and the context in which it functions, has not been assessed in the literature. How different types of changes influence RTC efficacy over a longer time period remains unknown. No papers have been found assessing the adaptability of RTC strategies to new situations nor has any research been published investigating the sensitivity of the performance of different RTC strategies to such new situations.

The above knowledge gaps are both practical and theoretical in nature and therefore form a barrier to the widespread implementation of RTC. Within these, there are several more specific underlying gaps, which have been highlighted throughout this chapter. They also form the basis of the questions and objectives set out in this thesis.

2.4. THESIS OBJECTIVE AND STRUCTURE

From the literature, the main research gaps were identified and form the basis for the research presented in this thesis. Those gaps are synthesised in the main objective of this thesis: To understand the influence of uncertainties on the performance of real-time control procedures applied to urban drainage systems. This objective is synthesised into the main research question:

Do uncertainties related to urban drainage models have an influence on the performance of the real-time control procedures?

To answer this main research question, several sub-questions are defined and addressed in each of the chapters contained within this thesis:

- *1- Can the performance of a real-time control procedure be objectively quantified?*

- *2 - What sources of uncertainty can affect the performance of real-time optimisation procedures?*

- *3 - Do rainfall prediction-induced uncertainties affect heuristic control procedures equally compared to real-time optimisation procedures?*

- *4 - Do long-term changes induced uncertainties affect the performance of real-time control procedures?*

2

The control procedures contained within this thesis will be confined to (weighted) volume-based control strategies. Given the relative lack of literature on the influence of uncertainties on control procedures within the UDS setting, focusing on either pollution or impact-based control strategies would exacerbate the uncertainties (given the uncertainties within the models relevant for those forms of control) and therefore complicate the analyses necessary. The methodologies presented within this thesis, however, could and should be expanded at a later stage to include different types of control objectives, to further understand the propagation of uncertainties within quality and impact models into the performance of control procedures.

2.4.1. THESIS STRUCTURE

The structure of the rest of the thesis is outlined below. The main body of the thesis is based on a number of publications (as indicated where relevant). In Figure 2.4, the mapping of the (sub-)research questions, related knowledge gaps and chapters can be found. Below, the structure of the thesis is presented in more detail.

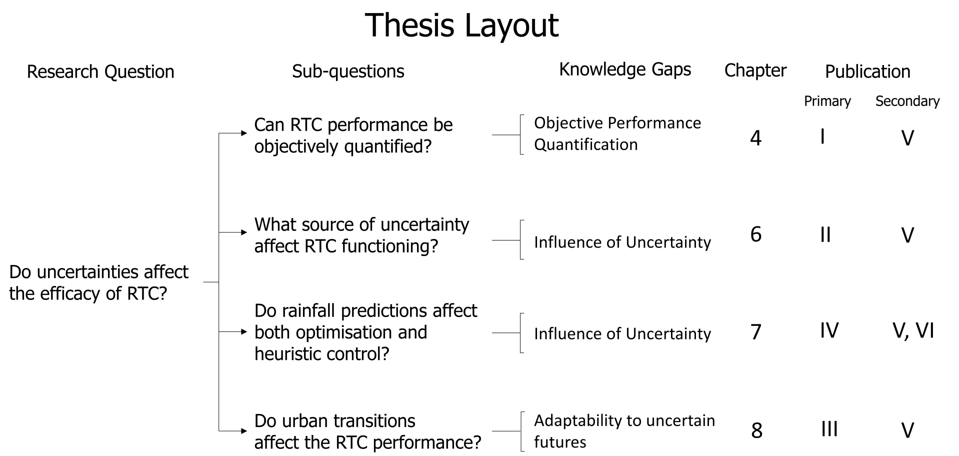

Figure 2.4: Graphical representation of the mapping of the key questions, knowledge gaps and the chapters in which they are addressed

To address the posed research question and sub-questions, case studies have to be selected. The case studies used in this research are detailed in Chapter 3. Previous and currently implemented real-time control procedures are also detailed here, forming the starting point or underlying control procedures in much of the research presented in this thesis. The other chapters are based on a number of peer-reviewed publications, the mapping of which is detailed in Table 2.3

Table 2.3: Mapping of the chapters and relevant publications based on the Paper ID specified in Figure 2.4

Paper ID	Title	Chapter	DOI
I	Quantifying the true potential of real time control in urban drainage systems	4	10.1080/ 1573062X.2021. 1943460
II	Real-Time Control of Combined Sewer Systems: Risks Associated with Uncertainties	6	10.1016/ j.jhydrol.2022. 128900
III	The Impact of Blue-Green Infrastructure and Urban Area Densification on the Performance of Real-Time Control of Sewer Networks	8	Under Review
IV	Predictive Heuristic Control: Inferring Risks from Heterogeneous Nowcast Accuracy	7	10.2166/wst.2023.027
V	Towards the long-term implementation of real-time control of combined sewer systems: a review of performance and influencing factors	2	10.2166/ wst.2022.038
VI	HAPPy to Control: A Heuristic And Predictive Policy to Control Large Urban Drainage Systems	5	Under Review

In Chapter 4, a performance metric is proposed, aimed at addressing the problems and gaps related to the communication of real-time control performances as identified in this chapter. The methodology set out there is aimed at answering the first sub-question detailed in the previous section.

A new control procedure, a Hybrid Heuristic And Predictive Policy (HAPPy), is then presented in Chapter 5. This part of the thesis deals with the ability to apply real-time optimisation procedures to large urban drainage systems with a number of actuators which makes the optimisation search space inhibitively large. The procedure is applied and tested in two different catchments to ensure transferability.

In Chapter 6, the effect of various forms of uncertainty on the performance of real-time optimisation procedures are assessed, as per the second research question highlighted above. The chapter highlights a methodological framework developed and tested to address the research question.

This is followed, in Chapter 7, by a more detailed analysis of the effect of rainfall prediction uncertainty on heuristic control procedures, as per the third sub-question. In this chapter, the focus is on both rainfall prediction statistics, analyse of the accuracy of various properties of the rainfall forecast, and the relative risks related to each of these identified properties.

In Chapter 8, the evolution of uncertainties related to transitions in the urban area is assessed, aimed at answering the final sub-question on the long-term transitions increasing the uncertainties and the potential effect on the efficacy of a stationary real-time control procedure.

The conclusions are presented in Chapter 9. Future research directions and practical implications of the research presented within this thesis can also be found in this chapter.

3
Case Studies

3.1. Introduction

Every urban drainage system (UDS) has a unique layout and characteristics, meaning that the generalisation of research findings can be difficult. This is particularly relevant in the context of RTC, as UDS characteristics drive the design, performance potential and implementation of the RTC strategy. To overcome this, the hypothetical catchment of Astlingen was proposed as a bench-marking tool for RTC procedures (Schütze et al., 2018; Sun et al., 2020b). However, focusing on a single, hypothetical case study can lead to a limited and biased research direction, making the widespread application of benchmark UDS problematic, as highlighted in the previous chapter.

Similarly, using a single case study leads to an inability to validate the transferability of conclusions. Here, the UDS associated with two cities in the Netherlands were used: (1) Eindhoven and (2) Rotterdam (see Figure 3.1). The UDS of the two cities vary significantly in size, layout, potential RTC objectives and number of actuators. Given this variety, the research presented here could be applied to distinct cases to further assess the transferability (or lack thereof) of the conclusions drawn, where practically possible. In this chapter, the details of both catchments are set out.

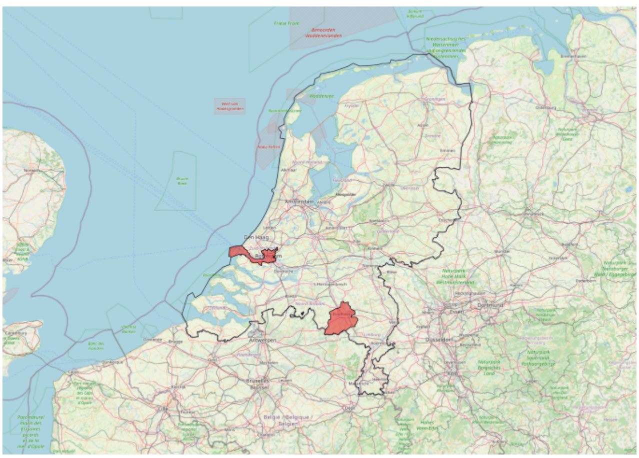

Figure 3.1: Location of the two areas used as case studies here: the WWTP Eindhoven catchment to the South and both WWTP Hoogvliet and WWTP Dokhaven in the city of Rotterdam (to the West) both highlighted in red

3.2. EINDHOVEN CATCHMENT

The wastewater treatment plant (WWTP) of Eindhoven is the 3rd largest treatment plant in the Netherlands, with a total capacity of 750,000 p.e. The WWTP serves the city of Eindhoven and surrounding municipalities to the north, east, and south. The wastewater influent arrives at the WWTP through three sewer networks: Nuenen-Son (NS, accounting for around 10% of the received inflow), Eindhoven Stad (ES, ~45% of the inflow) and Riool-Zuid (Southern Sewer, RZ, ~45% of the inflow). This thesis focuses particularly on the last of the three networks. Because of the size of the catchment discharging into WWTP Eindhoven, authorities influencing the decisions around urban water include various municipalities (responsible for the urban sewer networks), the waterboard (responsible for the treatment of the wastewater, large transport sewer and river water quality) and federal government (for the large canals in the system). Stakeholder conflicts might occur within the catchment, but will not be part of the analysis presented in this thesis (though is highly relevant when considering RTC implementation and leads to an interesting research direction).

The Eindhoven case study has been well documented in the literature, through various PhD works (Moreno Rodenas, 2019; Schilperoort, 2011; van Daal-Rombouts, 2017) and research papers alike (Benedetti et al., 2013b; Hadjimichael et al., 2016; Langeveld et al., 2013; Weijers et al., 2012). Any detail that might be missing from this thesis, as it was outside of the relevant information, can therefore likely be found in other sources. As part of the work done by Schilperoort (2011), a large monitoring network regarding precipitation, CSO water levels, river water quality and in-sewer water levels was set up (Figure 3.2 shows a global overview of the locations of various types of sensors).

Meandering through the Eindhoven area, the Dommel can be found as a small, lowland river, with a discharge ranging from 1-30 m^3s^{-1}, flowing from the north of Belgium through the Netherlands to join the river the Meuse towards the North Sea. Some 182 CSO structures can be found in the municipal sewer systems with an additional 3 in the main sewer trunks, discharging either into the Dommel directly, or in tributaries of the Dommel (Keersop, Kleine Dommel, Tongelreep or Run). Downstream of WWTP Eindhoven, the effluent from the treatment plant can account for up to 50% of the runoff during dry weather flow conditions, meaning the surface waters in the area have a high ecological and chemical sensitivity. Additionally, the urban waters are increasingly used for recreational purposes (for example, charity *city swims* are being organised in and by the city of Eindhoven and the downstream municipality of Den Bosch), meaning that the alleviation of pollution coming from the urban wastewater system should be reduced as much as possible.

3.2.1. URBAN WASTEWATER SYSTEM DETAILS

From the three WWTP inflows, the RZ sewer trunk spans the largest area. The RZ sewer trunk consists of a large transport line which collects wastewater from 15 different urban areas and is around 31 km in length. This transport line has a pipe diameter ranging from ø300mm at the upstream most end (at the municipality of Luijksgestel), to

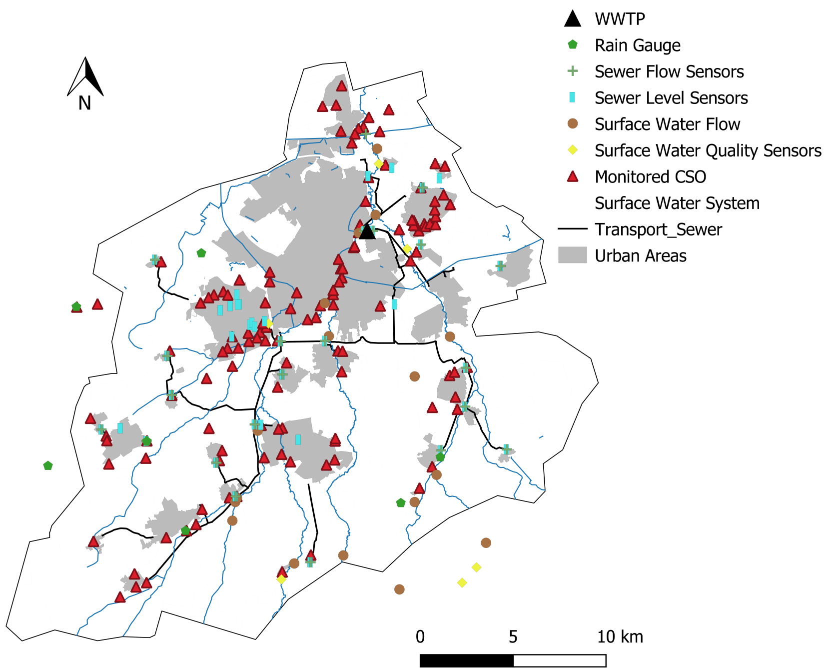

Figure 3.2: Overview of the catchment discharging into the WWTP Eindhoven and the monitoring locations

2250x1800mm at the discharge point at the treatment plant. A total of 59,000 m^3 of in-sewer volume exists in the transport pipe of the RZ sewer trunk, which can be activated by limiting the flow of three control stations (CS): CS Valkenswaard (the southernmost), CS De Meeren (downstream of CS Valkenswaard) and CS RWZI (just upstream of the treatment plant). Aside from the control stations, a pumping station is situated in the main sewer trunk to ensure that the wastewater and urban runoff can reach the treatment plant (see details on this pumping station in the following section).

The part upstream of the aforementioned pumping station, an area with a total population of 140,000, is the particular focus of this thesis and is shown in Figure 3.3. This area can be separated into three sections: from the pumping station to CS De Meeren (Section 1, servicing a total area of 8.0 km^2), from CS De Meeren to CS Valkenswaard (Section 2, servicing 4.4 km^2) and from CS Valkenswaard to the upstream most section (Section 3, servicing 2.7 km^2). The total in-sewer storage within the RZ network is 6.7 mm and an additional 4.1 mm of storage facilities can be found in the area.

All sections have large CSO structures which function as indicator CSOs and are activated when the respective sections are loaded with heavy rainfall. For Section 1, CSO Krooshek is located just downstream of the CS De Meeren (see Figure 3.3) and is indicative of the CSO volumes discharged from Section 1. Similarly, CSO Loondersweg, situated at the downstream end of the Valkenswaard municipal UDS and connected just

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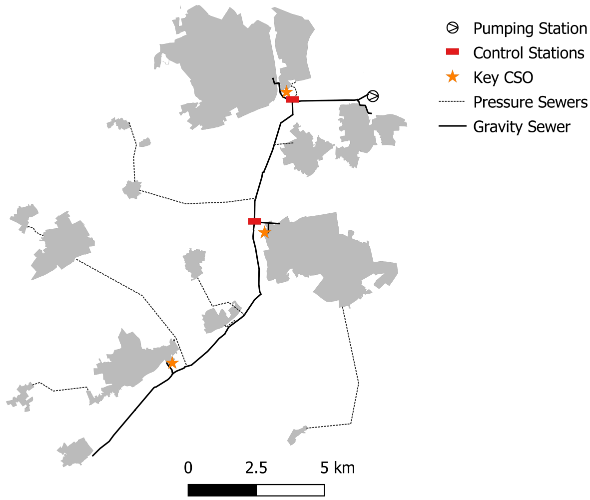


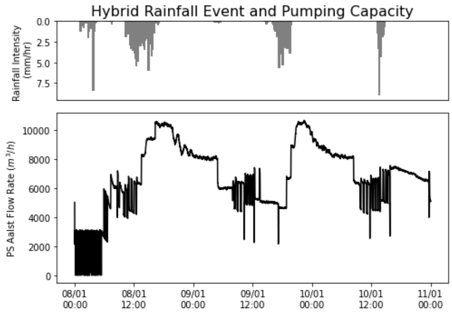
Figure 3.3: Overview of the Riool-Zuid Catchment of the Eindhoven WWTP catchment. Only the large transport sewer pipes are shown, the shaded areas indicated urban areas discharging into the municipal sewer systems

downstream of CS Valkenswaard, can be used as an indicator of the volume of CSOs discharged through Section 2. Section 3 was fitted with a large CSO structure in the municipality of Bergeijk (the largest urban area connected through gravity in Section 3), used as an indication of the total CSO load from the last section, following the methodology of the KALLISTO Project (see further details on the project in the section of previous RTC implementation).

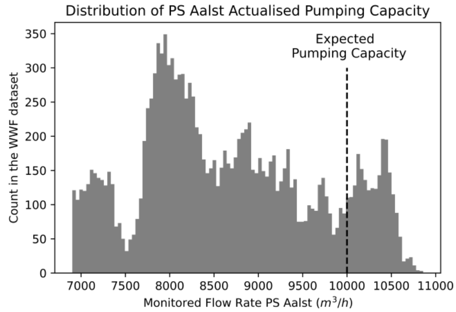
PUMPING STATION AALST

The key pumping station in the RZ sewer trunk is located north of the municipality of Aalst, aptly named Pumping Station Aalst (PS Aalst). PS Aalst consists of four pumps, discharging (when all pumps are activated) 10,000 m^3hr^{-1} through two ø1000mm pressure mains of approximately 3.1 km in length.

Although the target setting of PS Aalst is 10,000 m^3hr^{-1} (and the design capacity 12,000 m^3hr^{-1}), in practice this is not always reached. As both pressure mains are fitted with a flow rate sensor, the theoretical performance could be compared to the real performance. Typical behaviour that was observed is the decrease of flow rate during an event (highlighted in Figure 3.4(a)). Furthermore, in some events, the target flow rate is not reached at all. Taking a frequency analysis approach by assessing the frequency of recorded flow rates during wet weather conditions in bins of 50 m^3hr^{-1}, the highest frequency is observed around 8,000 m^3hr^{-1}, and the expected pumping capacity is reached significantly less frequently. The design capacity was never recorded in the dataset.



(a)



(b)

Figure 3.4: Details on the performance of PS Aalst. (a) a time series highlighting this variability during a rainfall event, and (b) shows the distribution of the observed delivered pumping rate

3.2.2. Current and Previous RTC Implementation

As mentioned before, a comprehensive monitoring system was set up in order to gain a better understanding of the functioning of the UDS (Schilperoort, 2011). Based on the continuous monitoring, an impact-based approach, relying on optimised rules of both the UDS and the WWTP, was proposed and showed a high potential for the reduction of both dips in the dissolved oxygen (DO) and peaks in ammonium (NH_4^+) in the receiving water bodies (Langeveld et al., 2013). This RTC implementation relied on the settings of the two control stations and the changes to the operation of the WWTP, details of which were also detailed by Weijers et al. (2012). Later, the "*Smart Buffer*" was developed, utilising the primary clarifiers (PCs) of the WWTP in a more efficient way (see van Daal-Rombouts et al. (2017)). Experiments have also been ongoing with direct aeration of the river (to avoid critical DO dips), though for technical reasons these have not been as successful as anticipated. Effluent aeration, on the other hand, has shown positive results in the oxygen balance in the river.

Aside from the impact-based control described above, the KALLISTO project was also initiated (Langeveld et al., 2013; Weijers et al., 2012). Part of this project looked at the re-balancing of the control stations in Riool-Zuid, given various flow rates delivered by PS Aalst. This showed a clear influence of the PS Aalst setting on the optimal settings. In the pre-KALLISTO settings, furthermore, the setpoints (set to limiting flow at CS De Meeren to 4,000 m^3hr^{-1} and letting CS Valkenswaard completely open) were sub-optimal leading to excessive discharged in the Valkenswaard (and CSO Loondersweg) area. Rebalancing these setpoints to 5,000 m^3hr^{-1} and 2,500 m^3hr^{-1} for CS De Meeren and Valkenswaard respectively, managed to reduce the overflow volume significantly (something that is reiterated and shown in more detail in Chapter 4).

Although the aforementioned historic control strategies have been impact-based, the control procedures developed have always been heuristic. Real-time optimisation procedures, which are a key part of the thesis, have not been applied. Owing to the question regarding the implications of uncertainties concerning RTC methods, it was chosen from here to focus, within the Eindhoven case study, on a volume-based approach to control, with equal weighting of all of the CSOs in the system. This also allows for the use of established open-source software packages, giving the flexibility which is required for real-time optimisation (Sadler et al., 2019). Furthermore, real-time optimisation requires a continuous understanding of the (new) initial conditions for which to solve the optimisation function, something which would require intimate knowledge of the receiving water body conditions and the sewer water quality in real-time. For this reason, an FH model was developed for the RZ branch first, merging updated data and models from the municipalities and the waterboard alike. This FH model was validated to function as expected (given the calibrations done in the creation of the models used for the development of the final, combined model) and used to develop and calibrate a simplified model.

3.2.3. Model Calibration

To assess and develop RTC strategies and procedures, well-calibrated yet sufficiently fast models are necessary. The development of these models is therefore advised to be the first part of the RTC development (Mollerup et al., 2016; Schütze et al., 2008). In previous development of real-time control methods, an integrated model was developed in the DHI WEST environment (Benedetti et al., 2013b). This model was further used to quantify sources of uncertainty within integrated models (Moreno-Rodenas et al., 2019). This model, however, takes a 0-dimensional approach to flow routing, meaning that the hydrodynamics within the system are potentially too simplified. The model can therefore miss key dynamics to a dynamic control aiming to utilise the hydrodynamics space within the system. For this reason, a model relying on at least a 1-dimensional simplification of the St-Venant equation is necessary.

As mentioned before, the FH model was established from well-calibrated models provided by the municipalities and the waterboard alike. These models, developed in the InfoWorks CS environment, were exported to an EPA SWMM5.1 (Rossman, 2015) and any errors were solved using a manual approach. The validity of the SWMM5 model was assessed by comparing the model output to the InfoWorks CS outputs. The FH-model of the Riool-Zuid system, however, has a high computational penalty (an hour simulation of DWF lasting over 2 minutes, for WWF this is over triple when run on a personal laptop) owing to over 10,500 nodes and 11,462 conduits necessary. For practical reasons, a conceptual, simplified model had to be developed in order to (1) perform real-time optimisation and (2) enable the offline optimisation of control procedures.

A conceptual model of the UDS upstream of the pumping stations was derived from a detailed hydrodynamics model and was built in EPA SWMM 5 (Rossman, 2015). For the conceptual model, the main transport line was kept as is, as the dynamics within this pipe are key to the overall system dynamics. The municipal sewers were replaced by storage units, in a similar approach taken in (van Daal-Rombouts et al., 2016). This conceptual model was calibrated against the validated data from the sensors in the UDS, using the predicted CSOs as a binary classifier combined with the Nash-Sutcliffe efficiency coefficient (NSE, Nash and Sutcliffe, 1970) of the level measurements monitored downstream and upstream of CS De Meeren and upstream of CS Valkenswaard and the

Table 3.1: Description of the locations of the monitoring data used for the calibration of the model, showing the ID, description of the location in the system and the parameter.

ID	Location	Monitoring Parameter
Mon. Loc 1	Upstream CS De Meeren	Water Level (m)
Mon. Loc 2	Downstream CS De Meeren	Water Level (m)
Mon. Loc 3	Upstream CS Valkenswaard	Water Level (m)
Mon. Loc 4	Pumping Station Aalst	Flow rate (m^3hr^{-1})

flow rate through PS Aalst, as the NSE is deemed to be a reliable measure for conceptual model calibration (McCuen et al., 2006). The parameters that were adjusted for the model were the initial loss term for each catchment, Manning's n value for the conduit in the transport sewer, runoff width for each catchment, and internal routing. The calibration was done automatically using a Genetic Algorithm with the maximisation of the mean NSE value over the four monitoring location as the objective (see Table 3.1 for the selected algorithm.

The focus of the calibration was to ensure that the dynamics in the transport sewer and the connected CSOs represented the UDS as per the monitoring data. Resulting of the calibration, the mean NSE value for the calibration events for the four monitoring locations varied from 0.57-0.78, with the validation events ranging from 0.32-0.73 (Figure 3.5). The overall best performance was for the flow rate at PS Aalst, indicating that the flows through the systems culminate to approximately the right values at the most downstream part. The lowest performance was of the water level upstream of CSO Krooshek. This monitoring location is set between two actuators and is highly sensitive to the behaviour of these actuators. With minor differences in the throughput of the actuators during WWF, large changes are expected. The relatively low NSE for the validation of monitoring location two is therefore acceptable as it relates to physical phenomena known in the system. The search space for the initial loss was 0-4mm, for Manning's n 0.005-0.015, the width of the catchment was 100-1000m and internal routing (100-1000m).

The occurrence of CSO events was another important calibration parameter. No false positives or negative events were found in either the calibration or validation stage, indicating that the model can correctly predict the occurrence of a CSO event at the various CSO locations. The timing of the increasing and decreasing limbs of the hydrographs predicted by the model is also found to be matching well with the data. Based on this calibrated model, the methodologies developed in the coming chapters will be tested. This model was also used as the internal-MPC model for the Eindhoven case study.

3.3. ROTTERDAM CATCHMENT

The city of Rotterdam is one of the largest cities in the Netherlands, with a population of around 625,000 inhabitants, situated in the delta where the North Sea, Rhine, Waal

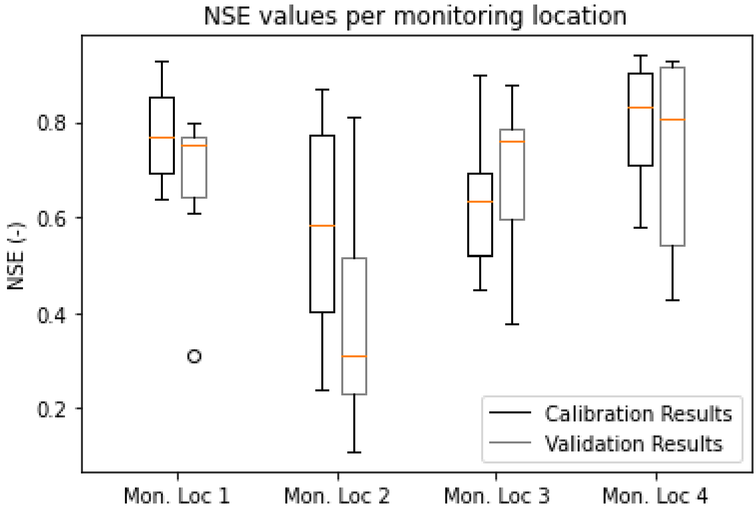


Figure 3.5: Calibration results for the four main monitoring locations

and Meuse come together. The Port of Rotterdam, one of the largest ports worldwide, is located in the Nieuwe Maas, the large river flowing through the middle of the city. Additionally, the city has several urban canals (so-called *singels*). Untreated discharge of wastewater into the urban canals (through CSOs) is considered to be significantly more problematic compared to discharging into the Nieuwe Maas (in numerical terms, it's been argued a factor of 10 should be used (Geerse & Lobbrecht, 2002)). Both the ecological sensitivity of the urban canals as well as the proximity to and utility by the inhabitants contribute to this. In the current RTC strategy implementation, roughly 37% of the total CSO volume is discharged to the urban canals and the remaining 63% to the Nieuwe Maas.

Three waterboards are responsible for the water quality around the city of Rotterdam: (1) *Hoogheemraadschap van Delftland* to the north-west of the city; (2) *Hoogheemraadschap van Schieland en de Krimpenerwaard* to the north-east of the city and (3) *Waterschap Hollandse Delta* to the south of the Nieuwe Maas. Additionally, the Nieuwe Maas falls under the Dutch Federal government (*Rijkswaterstaat*). The maintenance and operation of the UDS itself is the administrative responsibility of the city of Rotterdam. Similarly to the Eindhoven case study, this mix of stakeholders can be a challenge regarding the implementation of optimised control, through a change in discharges through catchments under the administrative responsibility of different institutions. Such stakeholder-related issues, however, won't be assessed in this case study (akin to the Eindhoven case).

In this thesis two of the five WWTPs and connected UDS in the city of Rotterdam are used: WWTP Dokhaven and WWTP Hoogvliet. The details per catchment are presented in Section 3.3.1 and 3.3.2 respectively and the generic layout of both systems can be found in Figure 3.6. A recent study presented by Langeveld et al. (2022b) details the implementation of a new, heuristic control strategy applied to the aforementioned UDS, the details of which can be found in Section 3.3.5. A third large WWTP is situated to the east of the WWTP Dokhaven catchment: WWTP Kralingseveer. The UDS system connected to this WWTP, however, was not included in the thesis. Given the similarity in size and layout with the WWTP Dokhaven UDS, the addition of the WWTP Kralingseveer UDS was unlikely to yield additional insights, whilst doubling the computational efforts required. On balance, it was determined to continue with only the two other WWTPs.

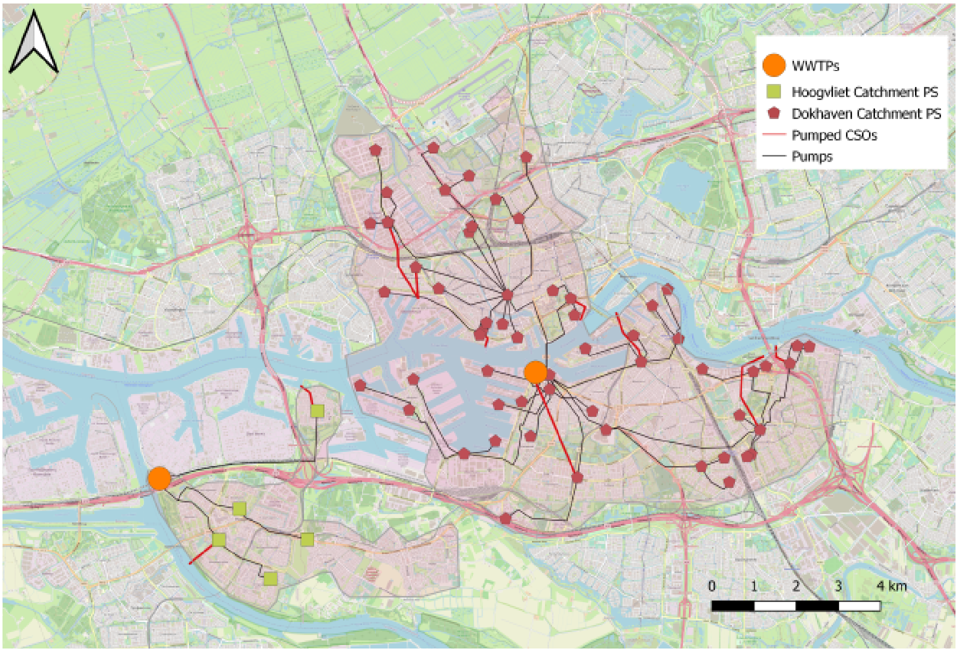


Figure 3.6: Overview and location of the two catchments used for the Rotterdam Case study: WWTP Hoogvliet (to the southwest) and WWTP Dokhaven (in the centre of the map). More details of both UDS can be found in Figures 3.7 and 3.8.

3.3.1. WWTP DOKHAVEN

WWTP Dokhaven is the largest of the treatment plants in the city of Rotterdam with a design capacity of 560,000 p.e. and a connected impervious area of 1,632 ha. A total in-sewer storage of 10.1 mm is distributed over 61 different sewer districts. The districts are distributed in several cascades, passing through several districts before ending up at the treatment plant. This can be seen in Figure 3.7, where the orange squares represent the sewer districts as linear reservoirs and the brown dots the CSOs. CSO events occur through both controlled CSO pumps and uncontrolled CSOs events over the CSO structures (the latter discharges to both the Nieuwe Maas and the urban canals, the former only into the Nieuwe Maas).

In line with the other UDS in the Rotterdam area, CSOs in the WWTP Dokhaven UDS discharge to both the urban canals and the Nieuwe Maas. The CSO pumps, which al-

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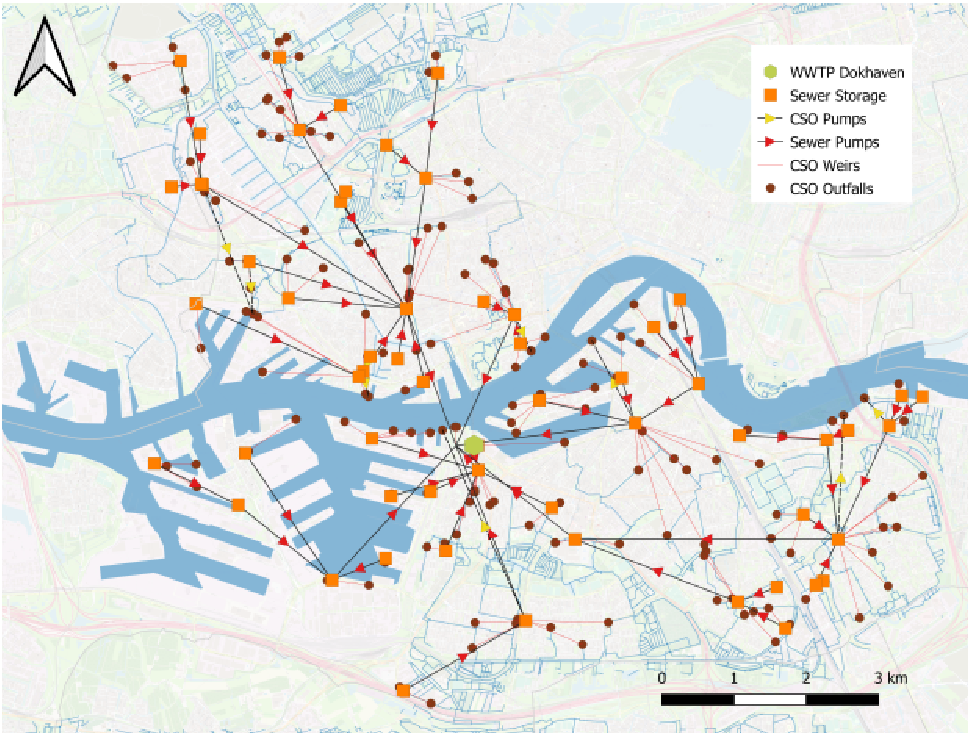

Figure 3.7: Schematic map of the location of the CSOs, districts and pumps for the UDS upstream of the WWTP Dokhaven. The sewer storage nodes shown here are representative of local sewer districts, lumped into a single reservoir

ways discharge to the Nieuwe Maas, account for roughly 50% of the total annual CSO emissions in the catchment following the currently implemented control strategy. These pumped CSOs (of which there are 8 in the UDS) have a combined capacity of 6.35 m^3s^{-1} (the equivalent of 1.4 mm hr^{-1}).

Another part of the control potential related to the WWTP Dokhaven case is the interaction between the sewer system and the treatment plant itself. The original treatment system was designed based on now deprecated standards. For this reason, additional control potential lies within the peak shaving of DWF diurnal patterns by retaining wastewater in the sewer system (similar to the control developed by Troutman et al. (2020)). Following the same rationale as in the Eindhoven case, however, this form of control is considered outside the scope of this thesis. The model of the WWTP Hoogvliet case is implemented in EPA SWMM5 using the virtual reservoir model (the structure of which is explained by van Daal-Rombouts et al. (2016)) of each of the districts.

3.3.2. WWTP HOOGVLIET

WWTP Hoogvliet is the smallest of the three large treatment plants in Rotterdam, with a capacity of 112,500 p.e. and a total connected area of 286.8 ha. It is located to the south of the Nieuwe Maas, situated among chemical industrial areas in the Port of Rotterdam. Five municipal districts discharge into the system (see Figure 3.8 for a schematisation), with a total in-sewer storage capacity of 10.7 mm. Two districts (22 and 27 in Figure 3.8) are fitted with pumped CSOs, enabling the direct discharge of diluted wastewater into the Nieuwe Maas (the use of which will be expanded on further in the next section), with a combined capacity of 0.72 m^3s^{-1} (or the equivalent of 0.9 mm hr^{-1}). The main industrial activity in the area does not discharge through the sewer system nor relies on the treatment plant.

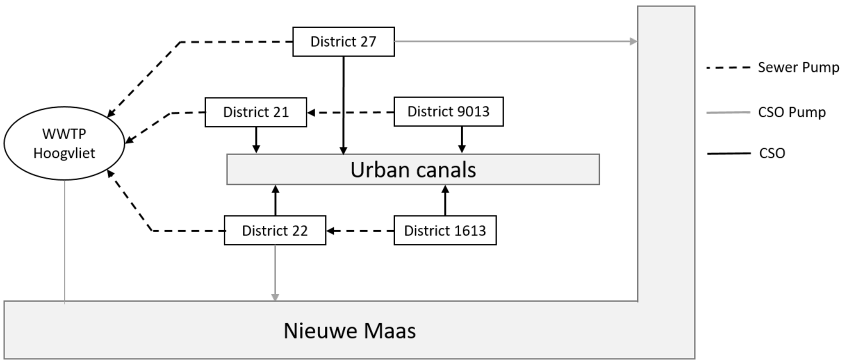

Figure 3.8: Schematic overview of the WWTP Hoogvliet catchment.

Because of similar physical constraints on the pumping stations compared to the WWTP Dokhaven case, the sampling interval for the change of the actuator set-points within the WWTP Hoogvliet UDS is set to 15 minutes. All the pumps within the system can be controlled and are therefore part of the control procedure, something which is equally applied to the WWTP Dokhaven case study real-time control procedure. The model of the WWTP Hoogvliet case is implemented in EPA SWMM5 using the virtual reservoir model (the structure of which is explained by van Daal-Rombouts et al. (2016)) of each of the districts.

3.3.3. LINEARISED MODELS AND MPC

To enable full centralised MPC for the case studies, a linearised version of the linked dynamic reservoir model from EPA SWMM5 is developed based on the linear reservoir tank used by Sun et al. (2020c). Every district in the catchments is described as a linear reservoir, where the water volume in the tank at the k^{th} time step is computed as:

$$V_k = V_{k-1} - (Q_k^{out} - Q_k^{in}) * \Delta T \tag{3.1}$$

$$Q_k^{out} = Q_k^{pump} + Q_k^{CSO} \tag{3.2}$$

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 generated and the 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. $V_{k-1} + Q_k^{in} - Q_k^{pump} > V_{max}$), Q_k^{CSO} is set to be equal to $V_{max} - V_{k-1} - Q_k^{in} + Q_k^{pump}$. This oversimplifies the dynamic storage but allows for rapid optimisation of the pumping capacities (the decision variables in the optimisation problem).

3

For an MPC system, the linear reservoirs are applied to all the districts of both the WWTP Hoogvliet and WWTP Dokhaven catchments to create a linearised model. For this optimisation model, the pumping capacities are the decision variables used to solve the objective function (see below). The optimisation only runs during predicted or occurring wet weather flow. The optimisation 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.

3.3.4. OBJECTIVE FUNCTION

As CSOs in all 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, characterised 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 prioritised. In previous work, sensitive areas are penalised 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 optimisation becomes:

$$\min(w_1 * \sum_{i=1}^{N_{a,NM}} \sum_{t=0}^{T_H} Q_{i,t}^{NM} + w_2 * \sum_{i=1}^{N_{a,CC}} \sum_{t=0}^{T_H} Q_{i,t}^{CC}) \tag{3.3}$$

where $N_{a,NM}$ 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, due to the real-time availability of rainfall nowcast, a horizon of 2 hours was chosen), $Q_{i,t}^{NM}$ is the overflow rate (in

m^3/h) of the i^{th} CSO structure discharging into the New Meuse river at time t, $N_{a,CC}$ 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 $Q_{i,t}^{CC}$ is the overflow rate (in m^3/h) of the i^{th} CSO structure discharging into the city canals at time t. Given that the objective function presented here only optimises the UDSs with regard to CSO volumes, the optimisation only runs when wet weather flow conditions are either predicted or observed (i.e. when rainfall is predicted or when anywhere within the UDS the filling degree exceeds what can be expected from wastewater only). This objective function forms the basis for the various control procedures (MPCs based on a genetic algorithm and linear programming and a novel control procedure) set out in Chapter 5.

3.3.5. CAS2.0

Resulting of the improvements in the control capabilities, the investments the city of Rotterdam has made in its urban water infrastructure, external pressures (i.e. climate changes) and increased awareness of sustainability (energy use and urban water quality), the city of Rotterdam has initiated a revision of the Central Automatic Control (CAS) protocol set up in the 1990s: the CAS 2.0 project. This project is meant to accommodate the various objectives set within the UDS and enable the optimal use of the urban water infrastructure in combination with allowing flexibility towards changing demands from the system.

CAS 2.0 is set up as a multi-layered control strategy, where different objectives are prioritised dependent on the stage each district is in, which is determined through the filling degree (FD) of the system. In this thesis, the strategy aiming at the reduction of CSO volumes to the city canals and Nieuwe Maas are considered as the sole objective, with the former having a priority of factor 10 as per Geerse and Lobbrecht (2002).

It should be noted that a key part of the CAS 2.0 strategy is the slow increase of WWF towards the WWTP, which was found to benefit the functioning of the WWTP. The inclusion of this particular objective was considered to be included, though, in a similar way to the Eindhoven case, this was found to potentially obscure the analysis. For this reason, a weighted CSO minimisation was used.

The CAS 2.0 programme relies on the definition of various *phases*, with each phase dependent on the water level in each of the sewer districts. The definition of those phases (listed below) and the set points related to those phases were determined through an optimisation procedure based on the simplified InfoWorks CS model of the Rotterdam UDS. Potential for improvement of the UDS operation, therefore, lies in making the set points and phases dynamic, either through real-time optimisation (here, in the form of model predictive control) or including rainfall predictions into the phase definitions.

The phases are also defined based on whether the UDS is *filling* or *emptying*. The phases I to VI (as defined below) relate to the duration in which the UDS is *filling*, whilst VII to XI refer to the stage when the UDS is *emptying*.

I. Filling degree above 0% in the pumping station: DWF Phase. In this phase, the pumping capacity is set to the maximum DWF capacity, to ensure that the total dis-

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charge towards the WWTP is below the critical level for normal process operations ($5{,}000\ m^3hr^{-1}$ for WWTP Dokhaven).

II. Filling degree of the UDS between 0% and 20%: Pumping stations continue at DWF capacity. This aims to reduce a sudden influx of loading to the WWTP to ensure continued normal operation.

III. Filling degree of the UDS between 20% and 50%: WWF_{min}. The pumping capacities are increased to 50% of the WWF capacity, aiming to slowly increase the loading of the WWTP.

IV. Filling degree of the UDS between 50% and 80%: WWF_{normal}. The pumping capacities of the pumping stations are increased to 100% of the WWF capacity, aiming to reduce the CSO volume by starting to empty the UDS as much as possible through the wastewater treatment line.

V. Filling degree of the UDS between 80% and 100%: WWF_{max}. The pumping stations are set to 100% of the WWF capacity. The CSO pumps are switched on, and the capacity from districts which do not discharge into the urban canals is switched off (or is reduced).

VI. Filling degree of the UDS above 100%: $WWF_{extreme}$. The UDS settings are the same as the previous phase, though the bypass at the WWTP is switched on, as well as the pumping stations regulating the water level in the urban canals. This aims to reduce the possibility of urban inundation by creating storage space within the urban canals for urban runoff.

VII. If the filling degree of the UDS is decreasing, but the previous phase was phase VI (filling degree above 100%): $WWF_{extreme}$ settings continue until a filling degree of 80% in the UDS achieved, after which phase IX will be initiated.

VIII. If the filling degree of the UDS is decreasing, but the previous phase was phase V (filling degree between 80% and 100%): WWF_{max} settings continue until a filling degree of 80% in the UDS achieved, after which phase IX will be initiated.

IX. If the filling degree of the UDS is decreasing, but the previous phase was either IV or the end of VII or VIII: WWF_{normal}. Sewer pumps are set to 100% WWF capacity until the UDS can return to phase I (DWF). Reduction in the discharge to the WWTP is not necessary as the dilution of the wastewater (given that the maximum recorded filling degree by definition was above 80% during the event) is sufficient to ensure no problems exist in the treatment processes at maximum hydraulic capacity.

X. If the filling degree of the UDS is decreasing and the maximum filling degree during the event was between 20% and 50% (phase III): WWF_{min}. The sewer pumps are set to 50% WWF capacity until the UDS is empty and returns to DWF operations (phase I).

XI. If the filling degree of the UDS is decreasing and the maximum filling degree during the event was below 20% (phase II): the maximum DWF capacity is maintained until the UDS returns to DWF operations (phase I).

To visualise the various phases, the CAS 2.0 logic was applied to a week (19th to the 27th of June 2016) with five rainfall events recorded in a nearby rain gauge (operated by the KNMI). The behaviour of both the pumping station (in black), sewer filling degree (in blue) and surface water (in red) are plotted in Figure 3.9.

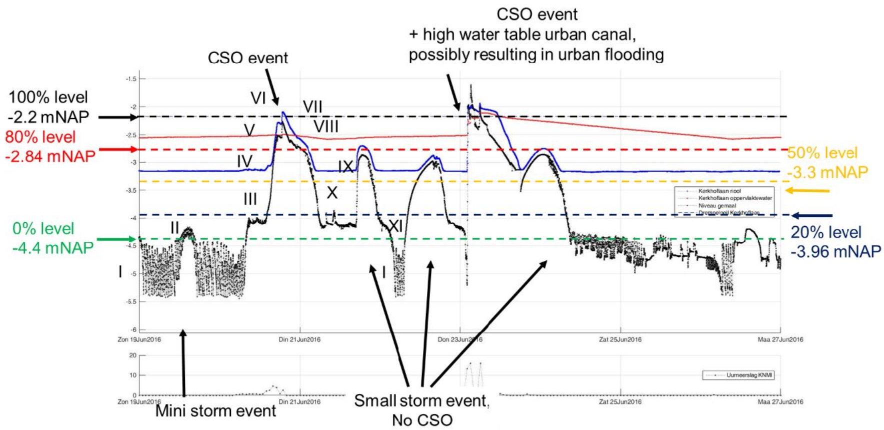

Figure 3.9: Example of the changes of the different phases during a multi-peak event. The coloured dashed lines indicate when, within the CAS 2.0 procedure, the phases change. The Roman numerals correspond to the phases outlined above. Figure is adapted from Langeveld et al. (2022b)

In practical implementation terms, the main logic of Levels 1 & 2 of the CAS 2.0 control strategy is a change in set points of pumping stations (by either (partially) switching off the sewer pumps to protect downstream districts or switching the pumped CSOs on) dependent on the upstream and downstream filling degrees (as per the phases outlined above). A graphical representation displaying this main logic is shown in Figure 3.10.

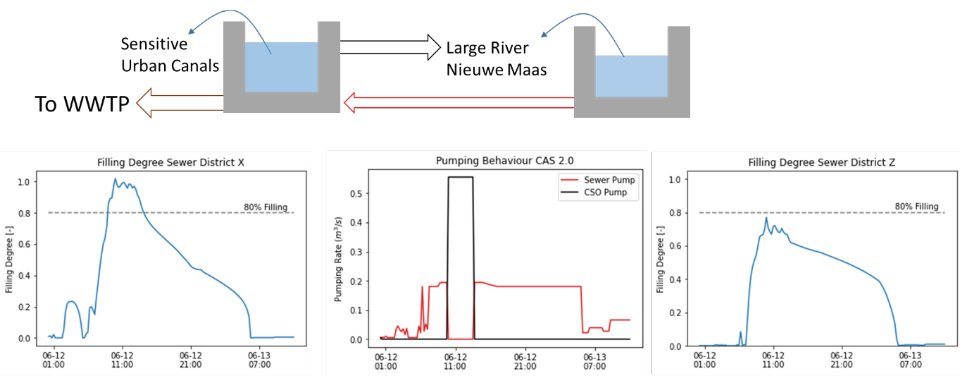

Figure 3.10: Representation of the main logic driving the heuristic rules of the CAS 2.0 project. It aims at protecting the urban canals by the reduction of inflow towards areas discharging into those canals and utilising CSO pumps to further decrease the discharge into the canals. This is at the expense of the Nieuwe Maas, a busy shipping river in the city of Rotterdam.

The control strategy was set up as a multi-objective problem, aiming to reduce the frequency and volume of CSO discharge to the urban canals first (with an importance weight of 10), then the total CSO volume (with an importance of weight 1). In Appendix C (Tables C.3 to C.5) the catchment, pump and control details are expanded on further for the WWTP Hoogvliet case. Detailed control rules for the WWTP Dokhaven case are not presented within this thesis given the extent of the rules (covering over 50 pumping stations) and the lack of clarity this would provide. The logic and implementation for this catchment follow the layout of the WWTP Hoogvliet case.

The set points for the CAS 2.0 project were determined based on an optimisation procedure applied to a simplified model representation of the catchments, which was implemented in the InfoWorks CS software. Each district was modelled as a virtual reservoir with the relevant static storage capacity modelled based on data from the full system (based on full-hydrodynamic model runs). The model was developed outside the work done within the thesis and was used for the development of the CAS2.0 rules. This InfoWorks CS model was exported to fit within the EPA SWMM5 model software. To simplify the implementation of the control procedure within the model whilst maintaining the flexibility of the multiple (frequency-controlled) pumps in the pumping stations, an adjustable orifice (of which the maximum flow rate can be set in InfoWorks CS and EPA SWMM5 alike) was used for control purposes of each of the pumping stations in the UDS (see Figure 3.11).

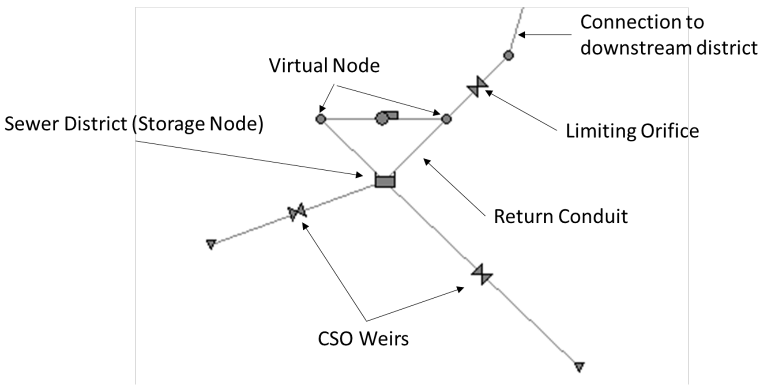

Figure 3.11: Overview of the implementation of the virtual reservoirs of the Rotterdam case studies in the EPA SWMM5 software

Upstream pumps would be connected at the virtual node within the virtual reservoir system. Stability criteria (predominately the Courant stability condition) were kept in mind in order to ensure the validity of the results given the relatively small spatial discretisation of the model in the given configuration (Pachaly et al., 2022). For the implementation of the control procedures developed hereafter, the Python interface PySWMM (McDonnell et al., 2020) was used.

4
Objective Performance Indicator

Based on the literature review, the need for a transferable reporting method, free of biases of previous sub-optimal operation, was highlighted (key gap number 1). Currently, to assert the efficacy of an RTC strategy or procedure, a comparison is made between the UDS operation before and after the implementation of the RTC strategy, considering a pre-defined evaluation parameter (e.g. the total CSO volume in a volume-based RTC approach, van Daal et al., 2017). Such comparisons are done at the design stage to establish if the control strategy improves the UDS or if additional measures are necessary (Dirckx et al., 2011) and to address regulatory adherence (Meng et al., 2020). The evaluation can be materialised by comparing the relative gains with the cost of infrastructural solutions with the same outcome (as done by, for example, Colas et al. (2004) and Beeneken et al. (2013)).

To improve the transferability of the results obtained in the RTC literature, a rating system, akin to the system used to rate the strength of chess players, was developed (Garbani-Marcantini et al., 2017), which was the first attempt to use a singular, transferable value to compare control strategies between different catchments. Although this method provides a more transferable evaluation, it is hampered by the same biases in previous sub-optimal operations and has lost much of its tangibility. This chapter set out the development of a new methodology to objectively assess the true potential of an RTC procedure, circumventing the inherent bias present in the current standard evaluation methods.

4.1. Methodology

The proposed methodology, similar to the current practice, estimates the expected performance of an RTC strategy for a set of rainfall events using a simulation model of the analysed UDS. This model is used to calculate the Realised Potential Indicators (RPIs) which are then used to identify the proximity of the RTC strategy to what could have been achieved (Figure 4.1). The calculation of RPIs is based on the concepts of generalised baseline (4.1.2) and the maximum theoretical performance (4.1.2). These two

This chapter is an adapted version of: van der Werf, J.A., Kapelan, Z. and Langeveld, J. (2021). Quantifying the true potential of Real Time Control of urban drainage systems. *Urban Water Journal*. doi: 10.1080/1573062X.2021.1943460

concepts are combined to form the RPIs, detailed in 4.1.3.

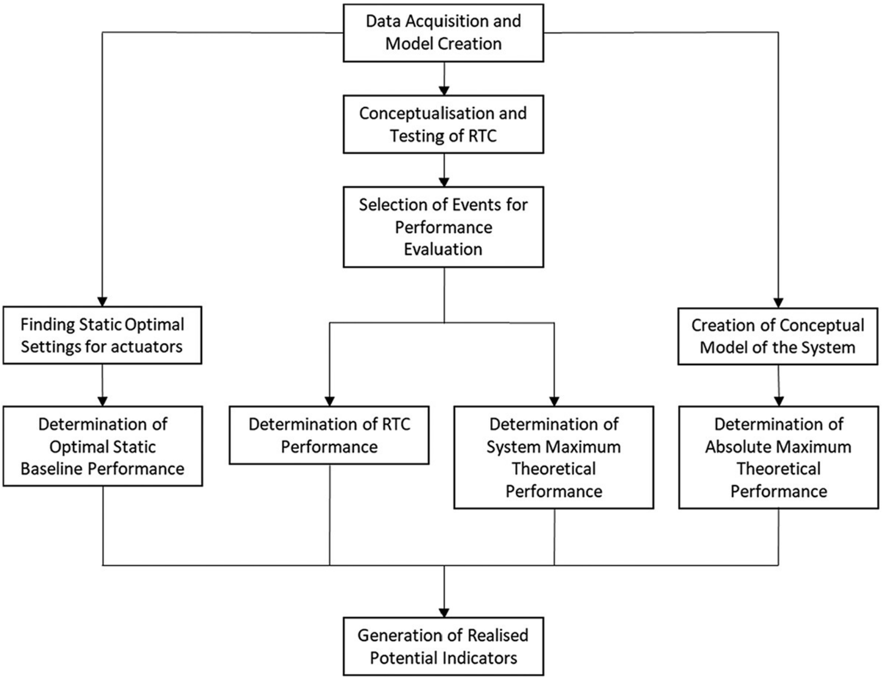

Figure 4.1: Schematisation of the methodology presented in this chapter, used for the unbiased quantification or real-time control performance

4.1.1. GENERALISED BASELINE

The generalised baseline performance is the performance of the analysed UDS based on predefined optimal fixed set points for all system actuators given a predefined RTC objective for a set of rainfall events. If the objective is to reduce the total CSO volume, the generalised baseline performance is the minimum CSO volume overall rainfall events achievable by having a single, fixed set point for each actuator. Any performance improvement above this static optimum performance is therefore the true potential of an RTC strategy.

The optimal static set points are defined here as settings under which the optimal performance of the UDS can be achieved. The static optimal settings are limited to a singular *if-then* rule, where a threshold is established above and below which the settings for each actuator are different. The optimal static settings are determined by solving the following optimisation problem:

$$\underset{Y(t),S(t)}{\text{minimise}} \sum_{k=1}^{N} J(Y(t), W(t), S_n(t)) \tag{4.1}$$

where J represents the relevant objective function chosen for the RTC strategy, N is the number of rainfall events used, Y is the sequence of system states at each time instance t, W is the sequence of disturbances at each time instance t and S_n are the settings of n system actuators defined as follows:

$$S_n(t) = \begin{cases} s_1, & \text{if } h_n \geq threshold \\ s_2, & \text{otherwise} \end{cases} \tag{4.2}$$

where s_1 and s_2 are the optimal set points, h_n is the variable of interest for the activation of n^{th} actuator and threshold is the triggering threshold. The optimisation decision variables are settings S_n. The optimisation problem defined in Equation 4.1 is subject to explicit constraints (lower and higher search limits for each decision variable) and implicit constraints (flow and energy balance equations implemented in the simulation model of the analysed UDS).

To solve the optimisation problem defined above, some optimisation method has to be used. Here, a standard Genetic Algorithm is used Goldberg, 2013 as it has widespread applications in water systems optimisation (Montserrat et al., 2016). As the optimisation can be done offline (i.e. prior to online RTC), computational limitations arising from optimisation are not important when compared to the RTC where optimisation is used online meaning that model accuracy does not have to compromise.

Once the optimal static settings for the control stations are determined, the RTC of the analysed UDS is simulated separately for each rainfall event by using these settings. The results from these simulations are then used to define the generalised baseline performance and are used to assess the performance per the steps set out in 4.1.3.

4.1.2. MAXIMUM THEORETICAL PERFORMANCE

Along with the generalised baseline, the Maximum Theoretical Performance (MTP) is calculated for each rainfall event. Two methods are proposed here to define the MTP, namely the absolute MTP and the system MTP. Both of these methods are conceptualised for volume-based RTC only as pollution- or impact-based RTC strategies are considered outside the scope of this paper. Having said this, if necessary and desired, it is straightforward to expand the MTP concept to these cases as well.

The estimation of absolute MTP is based on using a simplified model of the analysed UDS. This simplified model is a single linear reservoir model per pumped UDS which fill homogeneously throughout the event with relevant pumping capacity always available 4.2. The linear reservoir model is a mass-balance model of a section of a UDS (Gelormino & Ricker, 1994). This assumes that the filling degree of the UDS is equal throughout, using all the available storage capacity, which is the maximum potential performance for a volume-based RTC strategy. The total storage of the UDS, both static and dynamic, can be estimated through simulations of the full-hydrodynamic model (van Daal et al., 2017). The total CSO volume for each event used in the evaluation can be computed by solving the mass-balance equation for the simplified model. The UDS loading is the combination of the dry weather flow and urban runoff. The former is the total dry weather flow generated while the latter is computed by using linear superposition of the inflows for each sub-catchment in the UDS, calculated through the Rational Method (Butler et al., 2018).

When there are parts in the UDS which are connected through pumps to the main sewer or a downstream UDS section, then these parts of the UDS are modelled separately with their pump output considered as another component of the system loading. The most upstream part is modelled first, and if a CSO event occurs, this value is set as the minimum CSO volume for that part of the system. The part is then combined with the downstream or main UDS section, as per the central basin approach (Einfalt & Stölting, 2002) and the CSO volume is computed for the combined UDS sections. If this volume is lower than the upstream result, the upstream result is kept. This takes into consideration pumping capacities, which can influence the RTC potential if not included. If the stored volume is equal to the available storage capacity, the loss through CSO is equivalent to the difference between the system loading and the outflow to the WWTP (Figure 4.2)). This model considers CSO volume and flooding volume as the same and might therefore overestimate CSO volumes for events where flooding will occur. Events of this magnitude can therefore not reliably be assessed with this method. As RTC for CSO reduction has the greatest potential for relatively small events (e.g. Meneses et al. (2018)), this is not deemed inhibitory for its application.

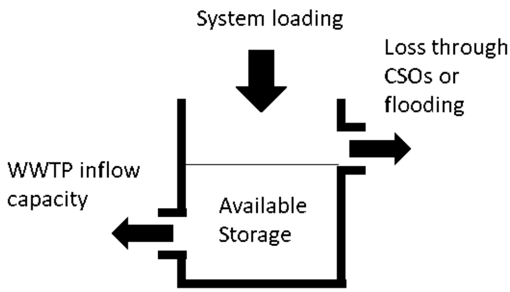

Figure 4.2: Schematisation of the Central Basin Approach

Note that absolute MTP assumes the potential of the RTC system to distribute the stored water homogeneously in the UDS without causing local CSOs. The system MTP, however, uses the model used for the RTC design or operation to compute, over the entire event horizon the optimal trajectory of settings for each actuator in the system following Equation 4.1 without the constraints imposed by Equation 4.2, thus acting as an MPC algorithm with a horizon of the event duration. It is therefore not assumed that all the storage in the system can be activated at any given time step, an assumption on which the absolute MTP is based. A large difference between the absolute and system MTP indicates that the effectiveness of the RTC to use the UDS optimally is limited with the current actuator configuration

4.1.3. RELATIVE PERFORMANCE INDICATORS

To allow for the comparison of RTC strategies for different UDS, two normalised realised potential indicators (RPI) are proposed based on an absolute and system MTPs respectively:

$$RPI_{absolute,n} = \frac{J_{so,n} - J_{RTC,n}}{J_{so,n} - J_{MTP_a,n}} \tag{4.3}$$

$$RPI_{system,n} = \frac{J_{so,n} - J_{RTC,n}}{J_{so,n} - J_{MTP_s,n}} \tag{4.4}$$

$$RPI_{absolute} = \sum_{n=1}^{N} \frac{J_{so,n} - J_{RTC,n}}{J_{so,n} - J_{MTP_a,n}} \tag{4.5}$$

$$RPI_{system} = \sum_{n=1}^{N} \frac{J_{so,n} - J_{RTC,n}}{J_{so,n} - J_{MTP_s,n}} \tag{4.6}$$

where $J_{so,n}$ is the objective function outcome for the n^{th} rain event in the set using the static optimal settings, $J_{RTC,n}$ the objective function outcome for the proposed RTC strategy for the n^{th} rain event, J_{MTP_a} and J_{MTP_s} are the objective function outcomes for the absolute and system maximum theoretical performance settings for the n^{th} rain event respectively, and N is the total number of events used. An RPI of 1 indicates that the RTC procedure has reached its maximal potential, where a 0 means no improvement to the performance compared to the baseline and a negative value signifies that the static optimal functions better compared to the RTC procedure. The distribution of the absolute RPI is computed using Equation 4.3 and the system RPI using Equation 4.4. The actual RPIs are defined as the RPI for the sum of the objective function outcome, as opposed to using the mean of the set of RPIs.

4.1.4. RAINFALL EVENTS USED

To assert the RPI values with confidence, sufficiently representative rainfall events should be included in the analysis. van Daal-Rombouts et al., 2017 showed the sensitivity of RTC performance if limited rainfall events are used. Kroll et al., 2018c used 24 rain events, varying from 0.1 - 3 year return periods as a representative sample. Schütze et al., 2018 however, used 10 continuous years of radar rainfall data. Both can be used, but a larger dataset remains preferable. If accurate radar data is available, capturing spatial heterogeneity of the rainfall, this data should be used.

Given the large area covered by the UDS, radar rainfall data was used as rainfall input to the system as spatial heterogeneity of the rainfall is an important factor influencing system response (Cristiano et al., 2019). The rain gauge adjusted radar data with a 1km x 1km resolution at a five-minute interval from the Royal Dutch Meteorological Institute was used (Overeem et al., 2009). For the simplified model, a weighted mean rainfall was used for runoff-generating catchments which spanned beyond a single pixel size. 103 Rainfall events were identified for the period of 2014-2020.

4.1.5. CONTROL PROCEDURES

To test the proposed assessment methodology, the case study of Eindhoven was used. As set out in Section 3.2, this case study has a long history of RTC implementation and therefore makes for a good case study to test the unbiased nature of the proposed RPIs. The minimisation of the total CSO volume in the UDS was used as the objective function for the RTC strategy. Several heuristic-based RTC strategies were developed to test the use of the RPIs for a real UDS (Table 4.1). All RTC strategies focussed on the use of the control stations to regulate the flow and relied on various levels of information integration.

Table 4.1: Overview of tested RTC strategies for the development of the RPIs

RTC Strategy Name	Description	Measurement Dependencies
Strategy 1	Phase-based adjustment of flow rates	Water level up- and downstream per control stations
Strategy 2	Phase-based adjustment of flow rates, adjusting for pumping capacity	Water level up- and downstream of control stations, flow rate through PS Aalst
Strategy 3	Continuous adjustment to difference in water level from a base level	Water level up- and downstream of all control stations to each control station

The principle of RTC Strategy 1 is to identify the flow phases in which the UDS sections upstream and downstream of the control stations are, and adjust the flow according to a predefined matrix per control station, where for every combination of phases an optimal set flow rate was calculated. The matrices are determined through the use of a Genetic Algorithm with search boundaries set to limit the computational time: 3000-7000 $m^3 h^{-1}$ and 1750-3500 $m^3 h^{-1}$ for CS De Meeren and CS Valkenswaard respectively. Each generation has a population of 15, with 3 parents used for mutation, selected based on the lowest total CSO across the used rainfall events. The phases are determined through the water level measurements upstream and downstream of each control station following set definitions (4.2). This allows the UDS to dynamically adjust to differences in the system while ensuring that the emptying of the UDS is not unnecessarily hindered by reducing the downstream flow (during the emptying of the system). The optimised set points can be found in Appendix A.

RTC Strategy 2 follows the same phase-based strategy as RTC Strategy one but adjusts the set points in the matrices depending on the measured pump rates of PS Aalst. For this, as opposed to a single predefined matrix per control station, three matrices were defined as applicable for the range 7000-8000, 8000-9000 and 9000-10000 $m^3 h^{-1}$ delivered by PS Aalst. The computation of these values followed the same procedure as RTC Strategy 1.

Table 4.2: Overview of the definitions used for the various flow phases in the UDS. The flow phases are used as thresholds within a heuristic procedure, where the set-points depend on the here-defined flow phases

Phase	Description
DWF	The water level does not exceed the set DWF boundaries
Filling	The moving average with a window of 25 minutes shows an upward trend great than 0.025 m/5min
Spilling	The water level exceeds a threshold set to 0.95 * CSO weir height
Stable	The water level is stable and below the spilling threshold (but above DWF)
Emptying	The moving average with a window of 25 minutes shows a downward trend greater than 0.025 m/5min

RTC Strategy 3 takes the static optimum as a baseline and adjusts the flow rate for the control stations based on an estimation of the filling degree in the upstream and downstream UDS sections. The filling degree is estimated by calculating the filling degree of the manholes up-and downstream of the control stations, upstream of PS Aalst and upstream of CSO Bergeijk. This gives two filling degree estimates per UDS section. the mean of these is used to estimate the overall filling degree in the UDS sections. If there is a difference in the estimated filling degree, the flow rate is adjusted depending on the magnitude of the difference as follows:

$$Q_{cs}(t) = Q_{cs\_so} + (FD_{ups}(t-1) - FD_{dws}(t-1)) * w_a \tag{4.7}$$

where $Q_{cs}(t)$ is the target flow rate for the control station at time t, Q_{cs_so} is the static optimal set point for that control station, $FD_{ups}(t-1)$ and $FD_{dws}(t-1)$ are the upstream and downstream filling degree at the previous time interval respectively and w_a is the correction severity constant.

The development of these realised potential indicators was done through the simulation of the aforementioned control procedures applied to the Eindhoven case study (see Chapter 3.2 for details). Noticeably, real-time optimisation control procedures (particularly MPC) are not included in a set of procedures used for the development of the indicators. This exclusion was done purposefully, to ensure the ability to analyse a relatively large data set, which is not realistic because of the computational penalty associated with real-time optimisation procedures. An MPC implementation for the Eindhoven Catchment was, however, developed and will be detailed further in Chapter 6.

Table 4.3: Performance Overview of the RTC Procedures

Control Procedure	Total CSO Volume (1000 m^3)	CSO Volume decreased compared to Pre-RTC	CSO Volume decrease compared to Baseline	Number of CSO events
Pre-RTC	592.3	-	-	46
Baseline	110.7	81.3%	-	34
RTC Procedure 1	90.9	84.6%	17.9	22
RTC Procedure 2	85.7	85.5%	22.6	21
RTC Procedure 3	60.1	89.9%	45.7	23

4

4.2. RESULTS AND DISCUSSION

The three RTC Procedures described in Section 4.1.5 were optimised using the same rainfall events used for the calibration of the model, implemented for all 103 events described in Section 4.1.4 and their respective CSO volumes were computed and compared. As described in Section 3.2 the pre-RTC operation of the UDS was to never restrict the flow through CS Valkenswaard and restrict, during wet weather conditions, the flow through CS De Meeren to 4,000 m3/h. As shown in Table 4.3, a significant system performance increase compared to the Pre-RTC performance was observed for all three RTC procedures tested in the study (Table 4.3) in terms of total CSO volume reduction.

The generalised baseline was obtained, where the static optimal settings were found to be 5,000 m^3/h and 2,500 m^3/h for CS De Meeren and Valkenswaard respectively. These static settings were used for the 103 rainfall events and the CSO values were computed. As it can be seen from Figure 4.3, in the pre-RTC situation, most of the overflow occurred through CSO Loonderweg (UDS section 2). This was alleviated in the generalised baseline by allowing more flow downstream and restricting flow upstream, resulting in increases in both other CSOs but compensated by the decrease in CSO Loonderweg, totalling $110.7 \times 10^3 m^3$, a decrease of 81.3%. Given this as the baseline to which the RTC Procedures are compared, the apparent performance improvements as per the conventional evaluation drop significantly (Table 4.3). The Pre-RTC system characteristics can therefore lead to over-estimations of the potential of RTC if, given that static optimisation can already significantly decrease the CSO volume emitted by the UDS.

When the absolute maximum theoretical potential for the UDS was calculated for the 103 events, CSO events occurred during six rainfall events over the assessed events in the main part of the sewer system, totalling $16.8 \times 10^3\ m^3$, or an 84.8% decrease in CSO volume compared to the generalised baseline. Given this large discrepancy between the MTP volume and occurrence of CSOs compared to the generalised baseline, significant improvements to the system performance are theoretically achievable using RTC. For the system's maximum theoretical potential, the total number of events went up to 10, with a total CSO volume of $37.2 \times 10^3\ m^3$.

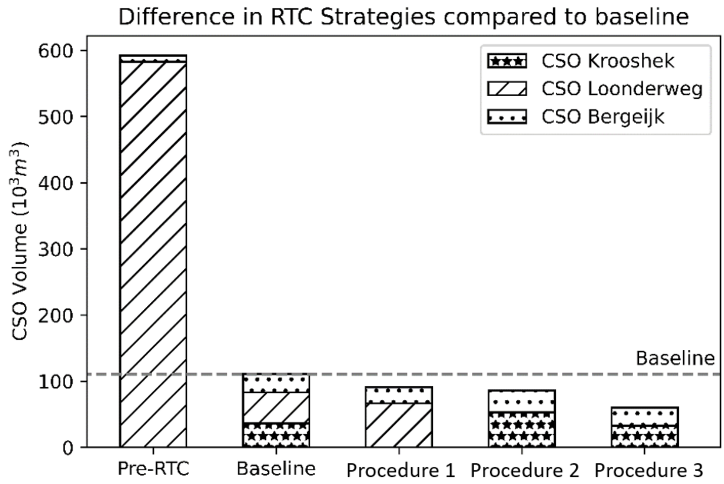

Figure 4.3: Objective comparison of RTC procedures to pre-RTC and generalised baseline

The absolute and system RPIs were computed for the three RTC procedures for each event. Events, where the generalised baseline did not experience any overflow ($n = 26$), were excluded from this analysis, as none of the RTC procedures caused any overflow during these events. As shown in Figure 4.4, the absolute RPIs are 0.21, 0.27 and 0.54 for the three procedures respectively. For the system RPI, the resulting values were 0.26, 0.34 and 0.68 for the three procedures. As expected, the system RPI are higher compared to the absolute RPI, as the absolute MTP overestimated the RTC potential given the current actuator layout. All RPIs are in the range between -1.38 to 1, indicating that for some events the additional measures have decreased the system's CSO performance. However, the mean and overall improvements offset these occasional decreases in performance.

Using the RPIs has shown that there is room for improvement of the RTC procedures in this case. Such improvements might be achieved through Model Predictive Control or other optimisation-based procedures, which were not included in this study. Given the relatively small difference between the system and absolute RPIs, this indicates that the current actuators are adequately able to achieve the theoretical optimal performance of the system. In the case where a large discrepancy between the MTPs is obtained, this would suggest the inclusion of additional actuators might be beneficial from a system performance point of view, to activate the under-utilised storage. Optimisation of actuators placement, as presented in Eulogi et al. (2020), can then be of interest. The use of both RPIs during the RTC evaluation process, therefore, gives additional information which can aid system operators in future investment decisions, through an increase in static storage potential or by aiming to reduce the gap between the system and absolute RPIs.

A decrease in the absolute RPI with an increasing mean total rainfall was observed

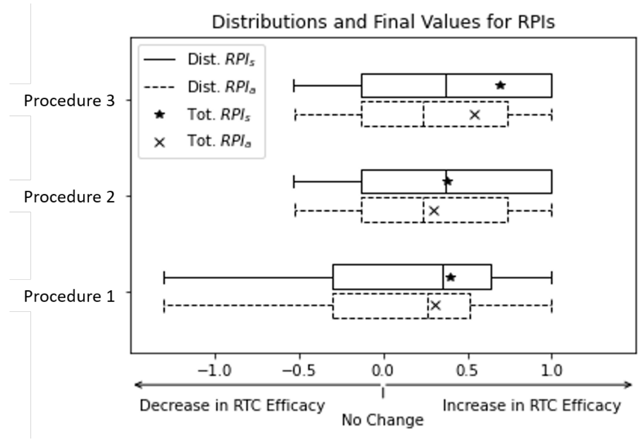

Figure 4.4: Assessment of the Performance of three procedures assessed

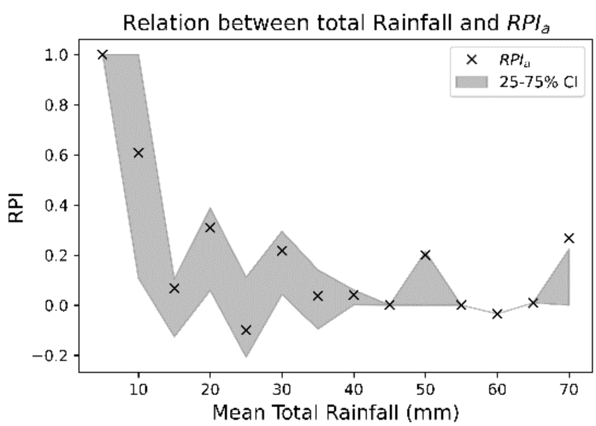

Figure 4.5: Assessment of the Performance of three procedures assessed

when averaging the absolute RPI over 5 mm intervals (Figure 4.5). This is consistent with the findings in the literature that reported the increased potential of RTC to mitigate against small to medium size rain events (Vezzaro & Grum, 2014). Although the rain events in this study did not include sufficient rainfall events in the 35 – 70 mm range to quantify this relation fully, the downward trend is significant.

4.3. CONCLUSIONS AND FUTURE OUTLOOK

This chapter proposed a new methodology for the more objective, cross-study comparison of Real-Time Control (RTC) procedures applied to urban drainage systems. A Realised Potential Indicator (RPI) was formulated, combining transferable definitions of the baseline and the maximal potential of RTC for an urban drainage system. The new methodology was applied and demonstrated on the case study of the southern sewer system of the Eindhoven wastewater treatment plant. Based on the results obtained the following can be concluded:

- Assessing the efficiency of some RTC strategy by comparing the urban drainage system's performance with that strategy to pre-RTC performance is not reliable and can lead to significant RTC efficacy overestimations. As such, this approach does now allow for cross-study comparisons of different RTC procedures;
- Using a generalised baseline approach in combination with a maximum potential threshold to calculate the RPI values suggested in this paper enables a more objective comparison of different RTC procedures and provides the means to assess the true potential of each RTC procedure given the analysed urban drainage system;
- Using the RPI-based methodology proposed here, additional insights can be gained into the performance of an urban drainage system and can be used to inform operators about future investment needs.

The results from this chapter show how the objective quantification of the efficacy of RTC of urban drainage systems can allow for better comparison of RTC procedure performances as well as gain a better understanding on how to improve the system in the future.

In future work, the RPI concept should be extended to include a formalisation for multi-objective functions and quality- and impact-based real-time control strategies. Testing of the RPI concept on different UDS using different control types, including model predictive control, should also be done to ensure the transferability of the concept. Explicit integration of uncertainty analysis in the methodology should be examined in future works. The RPIs will form the basis of the assessment of the control procedures throughout the rest of this dissertation (where applicable).

5

HAPPy to Control

REAL-TIME control performance potential was shown to be higher for real-time optimisation procedures compared to pre-determined heuristic rules (see Chapter 2). However, large catchments also suffer from higher computational penalties due to necessity for larger models and a larger search space for the optimal solution. To enable centralised MPC for larger UDS, (partial) linearisation or oversimplification of the UDS dynamics, resulting in a solvable optimisation problem, is necessary (Lund et al., 2018) but can introduce significant uncertainties into the internal-MPC model. This can result in the loss of control performance potential (as will be highlighted in Chapter 6) or requires the application of increasingly complex algorithms (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 optimisation as well as the complexity of the procedures and algorithms are clear barriers to the widespread implementation of MPC strategies. Using embedded non-linear internal-MPC models, which provide more interpretable handles for the optimisation, 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 optimisation 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 optimisation 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 optimisation 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.

In the chapter, the aim is to assess if the dynamics of the relative importance of actuators within a real-time control procedure change and can be predicted. It further aims to utilise this to combine heuristic and optimisation-based control. It proposes a methodology to enable near-global real-time optimisation of the operation of large and complex, non-linear urban drainage systems by reducing actuator dependency and

This chapter is an adapted version of: van der Werf, J.A., Kapelan, Z. and Langeveld, J.G. (*Under Review*). A Combined Heuristic and Predictive Policy (HAPPy) to Control Large Urban Drainage Systems. *Submitted to Water Resources Research*

aims to understand key dynamics emerging from the operation of combined heuristic and real-time optimisation control. The methodology proposed here will be applied to the case studies of the UDS connected to WWTP Hoogvliet and WWTP Dokhaven (see Chapter 3.3 for details).

5.1. METHODOLOGY

To circumvent the inhibitive computational penalty 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 is modular and consists of three stages: (1) the preparative steps, (2) the HAPPy procedure (which is the implementable control procedure) and (3) the evaluation stage (Figure 5.1a). The various preparative steps are outlined in the blue box, and each step is detailed in Section 5.1.1. and each step is outlined in the next section. The real-time optimisation procedure, hereafter the HAPPy procedure, follows an adjusted version of the MPC algorithm proposed by Sadler et al. (2019), as outlined in Figure 5.1b, The changes compared to the established MPC procedure structure are highlighted by dashed blue lines and further detailed in Section 5.1.2. All UDS modelling in this work was done using the EPA SWMM5 (version 5.1.015, Rossman (2015)) software and using the Python programming language interface PySWMM (McDonnell et al., 2020).

5

5.1.1. PREPARATIVE STEPS

The following section, highlighted in Figure 5.1a, sets out the offline steps within the HAPPy, to be done prior to the implementation of the real-time optimisation part (the HAPPy procedure). The policy is modular, meaning that any of the respective parts within the policy can be updated or 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.

OBJECTIVE FUNCTION, MODEL CALIBRATION 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). Firstly, an objective function has to be set up. The HAPPy can take any objective function related to control strategies (including CSO volume minimisation, weighted CSO volume minimisation, CSO pollution load minimisation, environmental impact minimisation, energy consumption or a combination). Here, a weighted volume-based minimisation function is defined, following the definition used by Vezzaro and Grum (2014):

$$min \sum_{i=1}^{N_a} w_i * \sum_{t=0}^{T_H} Q_{i,t} \tag{5.1}$$

where N_a is the number of actuators, w_i is the dimensionless weight associated with

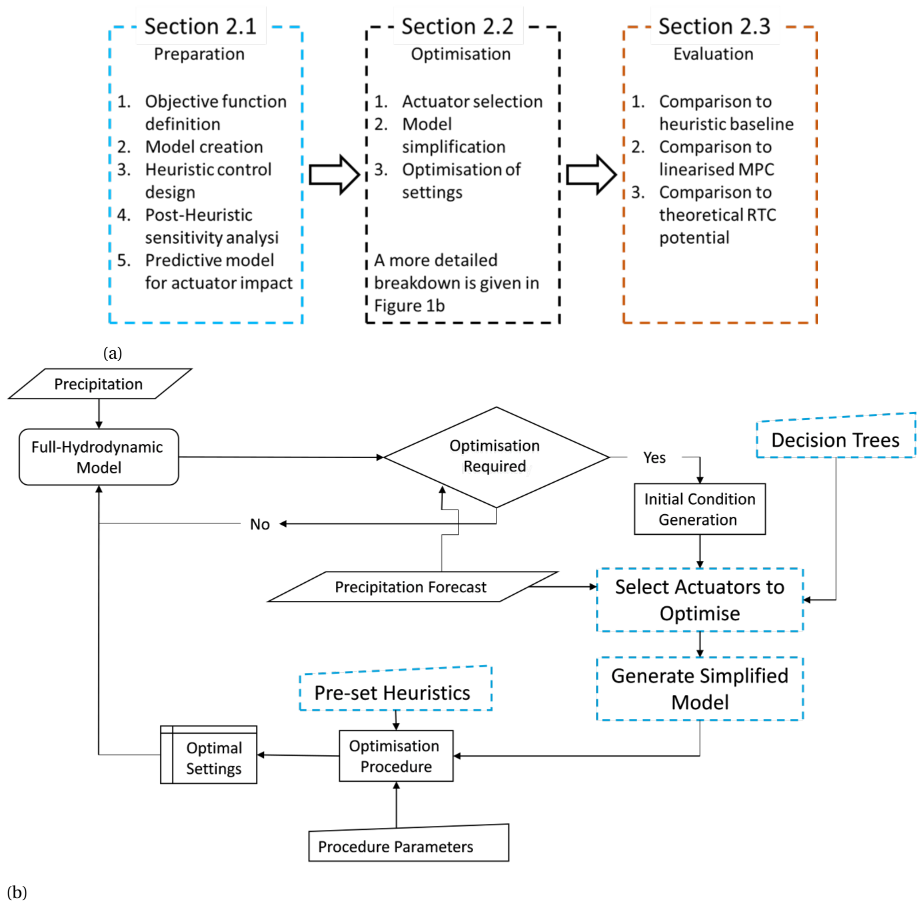

Figure 5.1: (a) Overview of the preparative steps of the HAPPy, the offline section highlighted by the dashed blue lines, the online procedure in black and the posterior analysis in red. This is followed by (b) the layout of the real-time optimisation part of the HAPPy: the HAPPy procedure.

the i^{th} CSO structure, T_H is the time horizon used in the analysis [s] and $Q_{i,t}$ is the overflow rate for the i^{th} CSO structure at time t [m^3s^{-1}].

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 (1) retain the key topological structure (determined by the layout of the actuators) of the UDS, (2) have a low computational cost, (3) describe the desired UDS dynamics, (4) it's initial conditions can be generated based on the real-time data and (5) include real-time rainfall forecasts as a forcing input. A set of virtual reservoirs lined through actuators is used here to represent the analysed sewer system. Each virtual reservoir is modelled 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 designed links representing pumps, orifices or other actuators. Virtual reservoir's outflow Q_s (See Figure 5.2) 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. The chose model structure needs to be calibrated to ensure the validity of simplified model outputs.

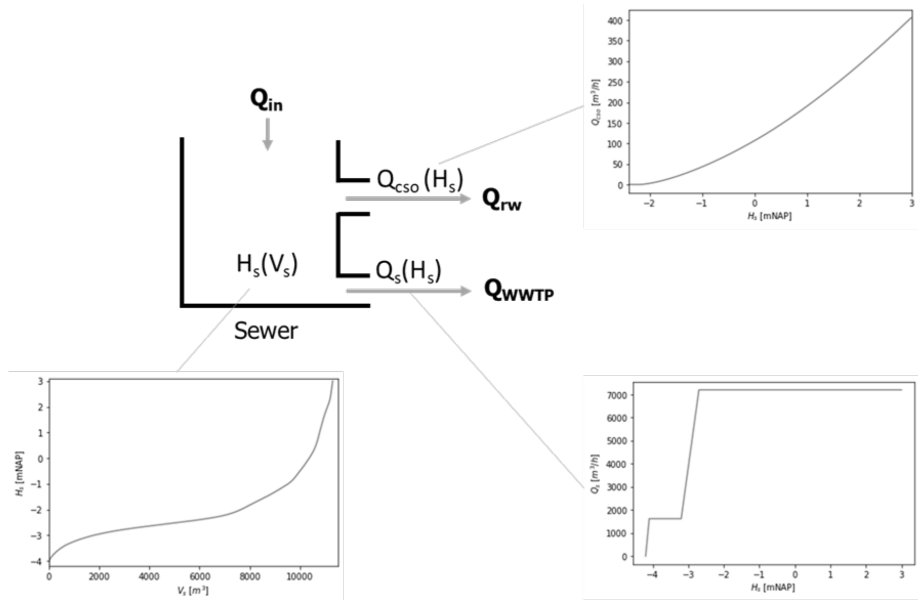

Figure 5.2: Schematisation of the dynamic virtual reservoir model used. Q_s either goes to the wastewater treatment plant (WWTP) (as per the example here), but can also connect to a downstream reservoir. Q_{in} contains these inflows, urban runoff and wastewater. Visualisation is adapted from van van Daal-Rombouts et al. (2016).

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 (Mollerup et al., 2016) and formal optimisation 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.

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 y_t saved as initial conditions and u_t as the rainfall forecast at time step t. Here, a perfect forecast was used to assess the maximum theoretical functioning 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 rainfall forecast 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 one hour was chosen, balancing the computational cost associated with GSA and the available real-time forecast used in RTC (two hours forecasts being available in real-time, updated every 5 minutes). 15 rainfall events (events defined as from the moment a non-zero rainfall depth is within an hour to when the UDS has returned to dry weather flow conditions).

The GSA uses a Monte Carlo (MC) type approach, sampling actuator settings using a Latin Hypercube technique, drawing values $\{k \subseteq \mathbb{R}^n \mid 0 \leq k \leq 1\}$ 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 MC simulation constitutes 1,500 model runs (in previous work, Benedetti et al. (2012) found 1,200 runs for the GSA in the wastewater modelling context sufficient).

For each run in each MC simulation, the objective function outcome 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 (MLR) between the actuator settings and the above difference in RTC performance is performed, generating a set of coefficient $C_i = \{c_{mlr} \subseteq \mathbb{R}^n\}$ where c_{mlr} are the MLR coefficients and n is the number of actuators in the system for the i^{th} 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 IC and FR, following $R_i = rank(|C_i|)$.

RANDOM FOREST OF DECISION TREES

To predict which actuators should be included in the optimisation 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 $\{N \subseteq \mathbb{Z} \mid 0 \leq N \leq A_n\}$ where A_n is the number of actuators in the system and N the number of actuators to be included in the optimisation 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 (ranging from 1 to 8) and assessing the RTC performance related to it. 8 actuators as a limit was chosen as a threshold to balance the range of options investigated whilst retaining the computational improvement of the HAPPy. The ranking results for each combined set of initial conditions and forecasted rainfall are then transformed into a binary dataset through:

$$BO_{n,i} = \begin{cases} 0, & if\, R_{i,n} > N \\ 1, & otherwise \end{cases} \tag{5.2}$$

where $BO_{n,i}$ is a binary value indicating inclusion (1) or exclusion (0) for the n^{th} actuator in the system at the i^{th} combined set of IC and FR given its rank $R_{i,n}$. These binary values are combined into binary inclusion sets, BIS, per combined set of IC and FR such that for all n actuators: $BIS_i = \{BO_{n,i}\}$.

The data, consisting out of 261 unique initial condition and forecasted rainfall pairs and the binary inclusion sets, is then (randomly) split into a training and validation dataset, 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 (RF) model was used. RF models have previously been shown to have the potential to accurately predict complex UDS dynamics (Montes et al., 2021). The RF model consists of 100 individually trained decision trees per actuator based on a randomly sampled subset of 50% of the training data to ensure the decision trees are trained on different sets of data. Each DT within the RF votes on the inclusion of the N^{th} actuator and the actuators with the most votes are selected for optimisation.

Due to the potentially skewed nature of the dataset decisions (relatively more actuators not selected compared to the selected), the F1-score is used to determine the predictive prowess of the random forest of the decision trees:

$$F1 = \frac{TP}{TP + \frac{1}{2}(FP + FN)} \tag{5.3}$$

where TP is the number of true positives, FP is the number of false positives and FN is the number of false negatives.

5.1.2. THE HAPPY REAL TIME PROCEDURE

When the offline section of the HAPPy is done, the real-time optimisation 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 optimisation) in the optimisation procedure, highlighted in Figure 5.1b, are expanded on. The procedure relies on the heuristic rules being applied to all the actuators, except for those selected using the RF method, which are optimised 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 Optimisation Required decision shown in Figure 5.1b).

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 schematised topography of the UDS, forming the basis of the internal MPC model as expanded in Section 5.1.1, 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 optimisable actuators. Based on the Random Forest model output, a subset of optimisable actuators $A \subseteq E$ is defined, where A has the size of the number of actuators selected by the decision tree (N). The internal model is then run following the heuristic procedure, with the lateral inflow time series per V defined as Inf_v.

A subset of the set of linear 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 linear reservoirs in V^*, every possible path to the most downstream node (usually the WWTP) is generated. For each path, the actuators included in the path are added to the set A and similarly, the linear 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 linear 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 5.3. This simplified internal MPC model can be run using the Inf_v and rainfall predictions as inflow to linear reservoirs in subset $V*$. This simplified internal MPC model is used to optimise the selected actuators, whilst the other actuators follow the predefined heuristic rules.

OPTIMISATION

The previously generated simplified internal MPC model is used to optimise the actuator settings following established MPC procedures (e.g. Sadler et al. (2019)). Any optimisation algorithm can be used for the optimisation process, but as the framework developed here is meant for both uncertainty reduction through information dependency reduction and the potential application of real-time optimisation of non-linearised UDS, it was decided to optimise the operation using the elitist genetic algorithm (GA). The reason for this choice is that GA is a well-established optimisation algorithm in the urban water literature and RTC (Rauch & Harremoës, 1999) and remains a popular optimisation algorithm in recent RTC publications (Abou Rjeily et al., 2018; Rathnayake & Anwar, 2019) and has the potential to be parallelised, enabling a better search for optimal solutions (Sadler et al., 2019). It can be applied to highly non-linear RTC problems (including impact-based RTC), making the application more generic. The hyper-parameters used for the GA optimisation are dependent on the simplified internal MPC model and the number of actuators selected through the HAPPy algorithm. Hyperparameter optimisation 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

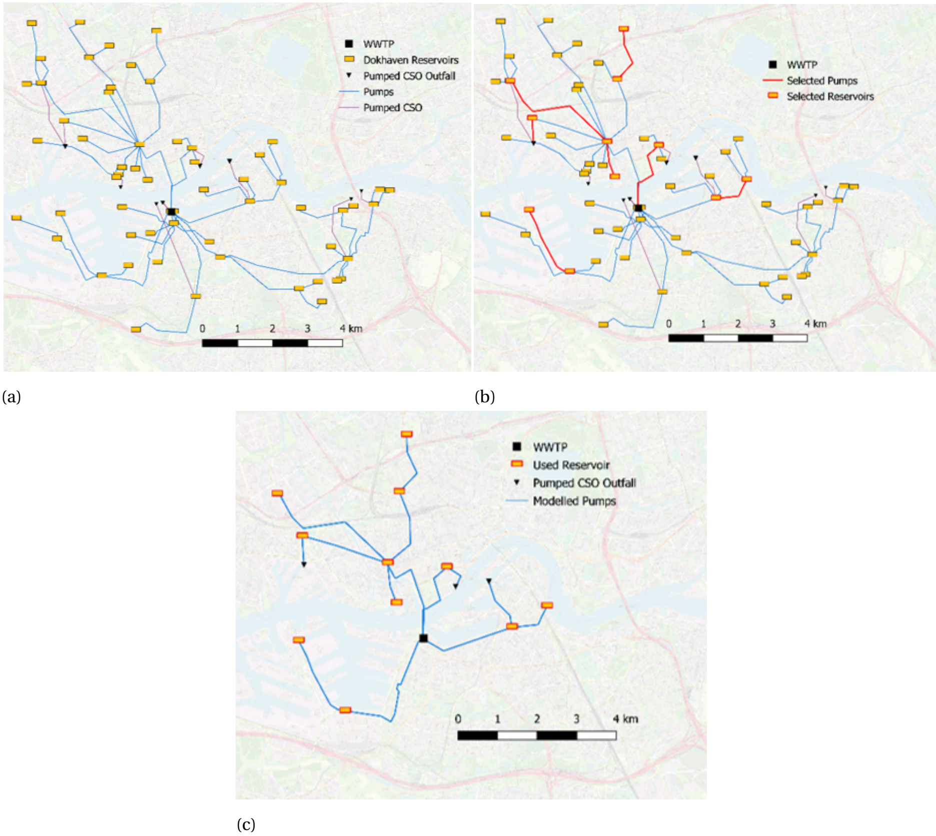

Figure 5.3: Here, the three stages of the model complexity reduction are shown. (a) shows the full model of virtual reservoirs connected through pumps, followed by (b) the pumps (actuators) selected for optimisation in red and (c) the topology of the final model. The final topology includes all selected pumps, as well as the pumps which can be influenced by the settings of the optimised 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 towards the WWTP (either directly or via downstream districts) or the pumped CSO outfalls (black triangles).

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.

5.1.3. PERFORMANCE EVALUATIONS AND MPC DETAILS

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, see Chapter 4) and the relative CSO volume (the ratio between the CSO volume using the RTC procedure and the statically optimised 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). The maximum CSO volume, calculated by assuming a perfect mass balance utilising the full-available storage of each sub-section or combined set of sub-sections over the entire rainfall event, of these computed volumes is used as the limiting factor, generating the maximum RTC potential per cascade in the UDS. A detailed breakdown of these steps can be found in Chapter 4. The static baseline here is the underlying optimised 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 linearised model was created to be used in a linearised MPC procedure (MPC-LP). 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 Chapter 3). Within this linear reservoir model, any inflow exceeding the 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, such as *on-off* pump decisions). In this MPC strategy, the optimal settings for all pumps in the system, $\mathbf{A_n}$, are computed and the first instance over the horizon for each actuator is implemented in the representative UDS model. The performance of the HAPPy procedure is compared to the performance of this linearised MPC, using the linearised model as an internal-MPC model, the COIN-OR solver (originally developed by Lougee-Heimer (2003)) as an optimisation algorithm and the original model of connected virtual dynamic reservoirs as the representative model of the UDS. The details of the linearised models used here can be found in Chapter 3.

The performance of the HAPPy is also compared to an MPC procedure based on a genetic algorithm (MPC-GA) for the WWTP Hoogvliet case using the virtual (non-linear) reservoirs as the internal-MPC model. GA was not a viable optimisation method for the WWTP Dokhaven case, given the relative search space. This MPC follows the structure described by Sadler et al. (2019), using the GA details highlighted in Table 5.1. The optimisation function is subject to implicit constraints (mass and energy balance equations implemented in EPA SWMM5) for the MPC-GA and the MPC-LP was subject to the modelling constraints set out in Section 3.3.3. The objective function can be found in Section 3.3.4 (Equation 3.3). Here, the same vector representing the control handles, $\mathbf{A_n}$, is calculated and are implemented when derived.

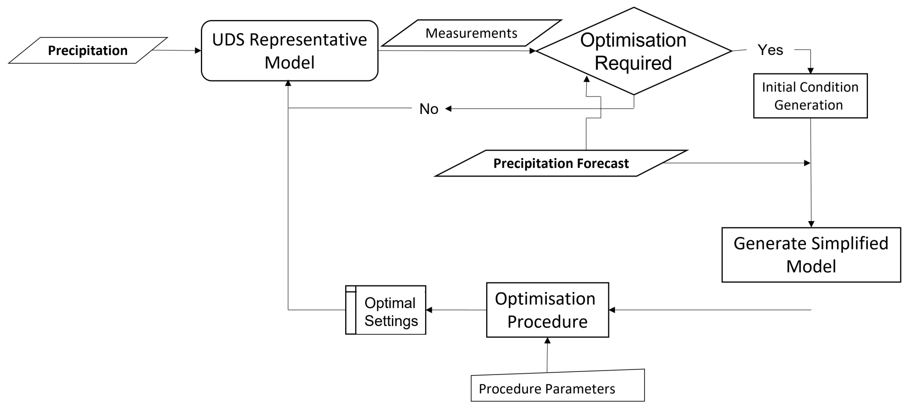

Figure 5.4: Schematisation of the MPC procedure. A model representing the UDS is used, from which the state of the system is determined. This is used to generate a simplified model, which is optimised using either a genetic algorithm or linear programming (COIN-OR cut-and-branch) solver, dependent on the model.

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Table 5.1: Overview of the details of the GA-based MPC for the WWTP Hoogvliet case study

Variable	**Value**	**Description**
Forecast Horizon	1 hour	
Forecast Type	Perfect	Using observed rainfall as the forecast
GA – population size	50	
GA – parent portion	0.16	
GA – mutation probability	0.1	
Sampling Interval	15 minutes	

A comparison is also made to the real-time optimisation of the settings of the N-actuators which have the highest frequency of “most important” (i.e. the HAPPy procedure without the dynamic selection of the relevant actuators). This statically selects the actuators for the optimisation (SSAO run) procedure and was used to assess the relevance of the dynamic selection of the actuators within the proposed procedure.

5.1.4. RAINFALL EVENTS

To capture the spatial heterogeneity of the rainfall events, radar data was used. An open dataset 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 at a 1km x 1km raster with a temporal resolution of 5 minutes and is a merged product of a network of rain gauges and radar data from Dutch, German and Belgium radars.

As mentioned before, the application of this methodology was tested on both the UDS of WWTP Hoogvliet and the UDS of WWTP Dokhaven. For the evaluation of the HAPPy procedure implemented in the Dokhaven catchment, 8 rainfall events from 2020 were selected. The weighted mean rainfall over the catchments ranges from 6.77 to 33 mm (mean 19.37 mm), with maximum intensity and duration ranging from 6.75 to 52 mm/hr (mean 18.49 mm/hr) and a total duration ranging from 3.28 to 11.86 hr (mean 7.71hr), respectively. 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. The number of events was limited to those reported here, as a single real-time optimisation run takes around 12 hours.

The events considered for the WWTP Hoogvliet catchment, on the other hand, were larger with a mean depth ranging from 14 to 43 mm (mean 25.3 mm), a maximum intensity ranging from 10.9 to 40.9 mm/hr (mean 26.4 mm/hr) and a total duration ranging from 5.6 to 10.8 hours (mean 8.67 hrs). These events were selected in order to test the performance of the HAPPy under scenarios which have a low potential for optimisation 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, 2022). More details of all the rainfall events (for both catchments) are included in Appendix B (Tables B.1 and B.2).

The observed radar data is also used as the forecasted rainfall used within the (simplified) internal-MPC model, in order to minimise the uncertainties and highlight the theoretical performance potential of the HAPPy. This is done for all real-time optimisation 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 linearised MPC, where the first step is the calculation of the lateral inflows following the EPA SWMM rainfall-runoff calculation).

5.2. 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 analysed catchments. Then, the performance of the HAPPy procedure is compared to a static form of real-time optimisation and a full MPC procedure applied to the smaller UDS to benchmark the HAPPy functioning. Then, the HAPPy procedure, using a differing number of actuators to optimise, is applied to the larger UDS and the key dynamics observed are discussed. Two events are further examined to highlight the function of the HAPPy procedure.

5.2.1. ACTUATOR RANKING

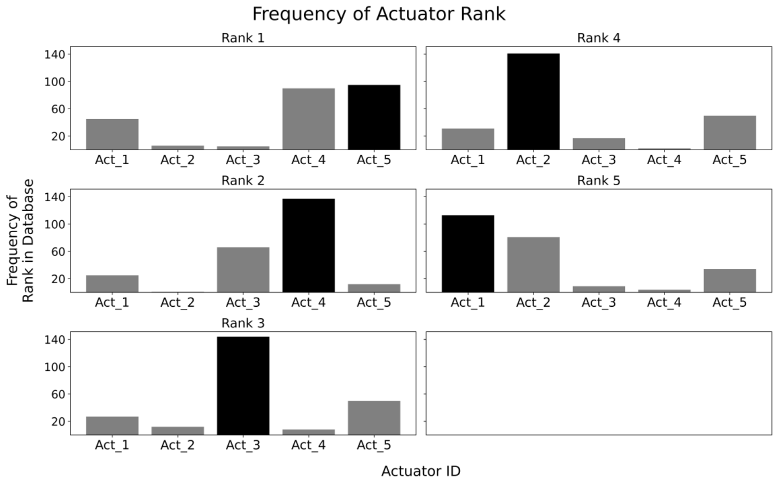
Dynamically selecting the most influential actuators in the system assumes *a priori* that this changes during and for different rainfall events. The importance of each actuator was determined using the methodology described in Section 5.1.1, i.e. based on the 261 (based on 15 rainfall events) binary 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 catchment and ranks 1 to 51 for the 51 actuators in WWTP Dokhaven) are shown here in Figure 5.5. 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 case (Figure 5.5b), 21 actuators were not found to be relevant as these were never present in the top 10 ranked 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 decision trees generated for this reason.

5.2.2. PREDICTION OF USEFUL ACTUATORS

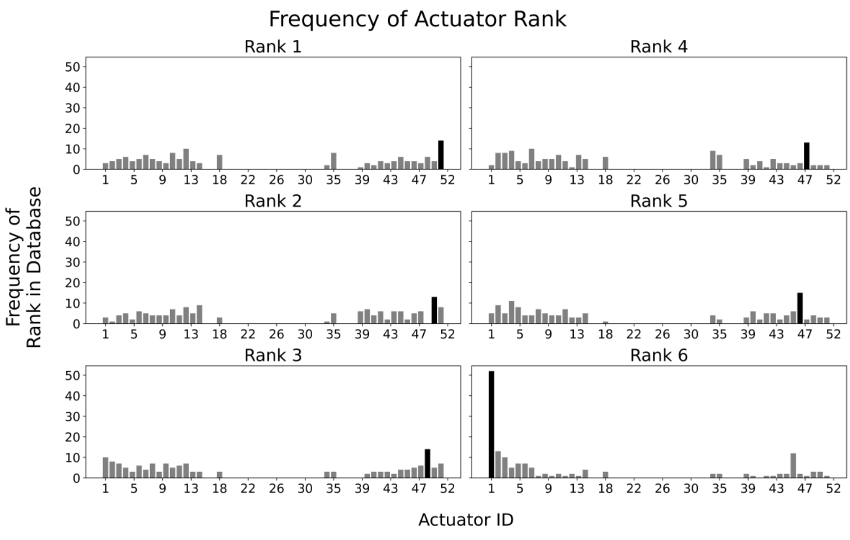
The ability to correctly predict the impactfulness of the actuators is a key step to ensure the functioning of the HAPPy procedure. For the WWTP Hoogvliet UDS (with five actuators) the validation results indicate that the random forest method is able to accurately predict 3 actuators with the highest 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. The performance of the prediction related to the identification of the 6 actuators (20% of the total actuators) with the highest level of impactfulness for WWTP Dokhaven (out of 51 actuators, 30 of which are included in the creation of the random forest as the other 21 were never within the top 10 highest ranked actuators) a lower performance was observed compared to the smaller catchment, with an F1-score of 0.72. 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 ($\frac{TP}{TP+FN}$). 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.

5.2.3. RESULTS – WWTP HOOGVLIET

The HAPPy procedure, with three (out of 5) actuators included in the optimisation, was benchmarked against a real-time optimisation procedure using the three most impactful actuators (highest mean rank from the GSA) of the UDS (statically selected actuators optimisation, SSAO), a full MPC procedure based on the linked dynamic reservoir models and a genetic algorithm for optimisation (full MPC (GA), using all actuators in the optimisation procedure), and a full MPC procedure based on the linearised model using linear programming to optimise the UDS (full MPC (LP), using all actuators in the optimisation procedure). The HAPPy procedure reduced the total overflow in the catchment by 5.41% for the seven events analysed when compared to the optimised baseline (Table 5.3). This is relatively low compared to the previously reported RTC performance levels (see Chapter 2 and Quaranta 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 max-



(a)



(b)

Figure 5.5: 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 optimisation.

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Table 5.2: Confusion matrices of the random forest results as applied to the validation dataset of both of the catchments studied here. The incorrectly predicted values are highlighted in red, the correctly predicted ones in green.

		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%

imum reduction potential through RTC (the CBA value) of 14.45%. For the two smallest rainfall event within the dataset, a reduction of 18.5% relative to the optimised 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 optimise (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 optimisation algorithm performing slightly better. The model simplification through linearisation therefore did not significantly decrease the real-time control performance and the genetic algorithm managed to equally optimise the operation of the UDS compared to the linear solver.

Table 5.3: Results for the different control procedures. The baseline refers to the heuristic control procedure developed under the CAS2.0 project.

	Baseline	**SSAO**	**HAPPy**	**Full MPC (GA)**	**Full MPC (LP)**	**CBA**
CSO Volume ($1000 m^3$)	285.9	276.1	271.1	269.9	270.1	249.8
Reduction cf. Baseline	-	3.55%	5.41%	5.93%	5.84%	14.45%
aRPI	-	0.27	0.41	0.44	0.44	-

To better understand the performances of the three optimisation-based RTC algorithms, the distribution of the pumped, unpumped and total CSO volumes for the seven rainfall events were analysed (Figure 5.6). As can be seen from this figure, the HAPPy procedure performed better compared to the procedure which relies on the real-time optimisation 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 prioritised (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 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.

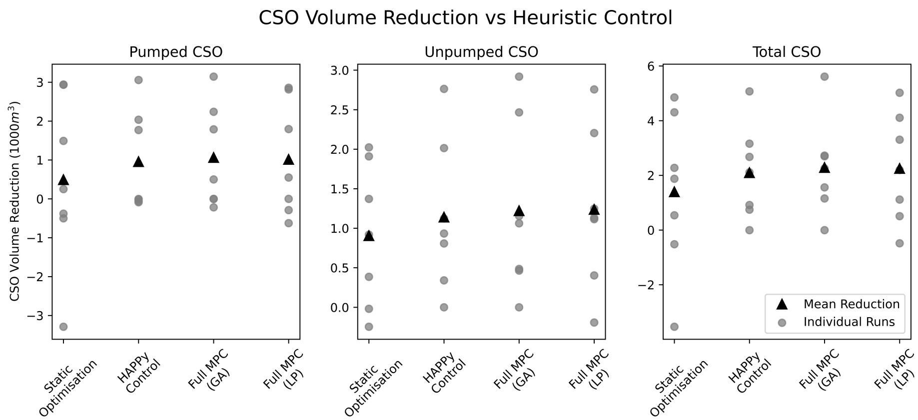


Figure 5.6: Comparison between three optimisation forms for the Hoogvliet catchment: Statically Selected Actuator Optimisation (using the global most import actuators), HAPPy algorithm (dynamically selected actuators) and Full MPC (using all actuators). Whiskers represent the 25-75% interval and circles the outliers

When compared to the full MPC systems, the HAPPy approach performed only slightly worse, with the genetic algorithm-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 Kolmogorov-Smirnov two-sample tests) in the distributions of the overflow volume reductions, comparing the SSAO, HAPPy and the two full MPC procedures, were not found (Figure 5.7. There was no significant difference in the total CSO volume, CSO volume to the New Meuse nor the CSO volume to the city canals.

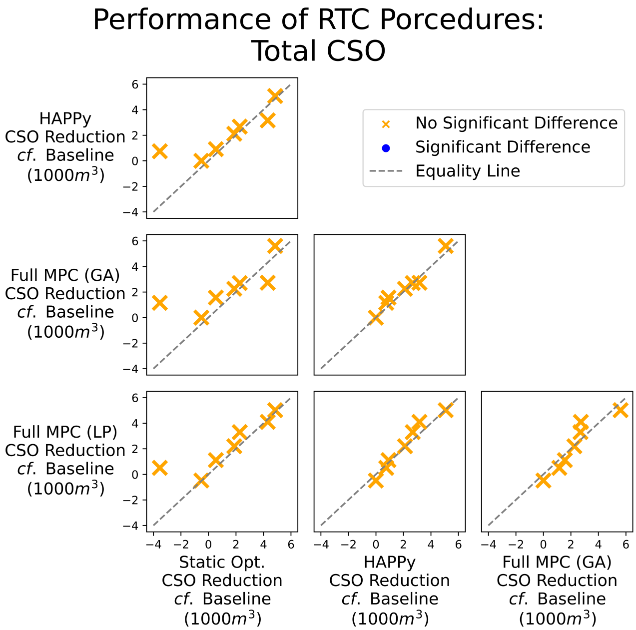
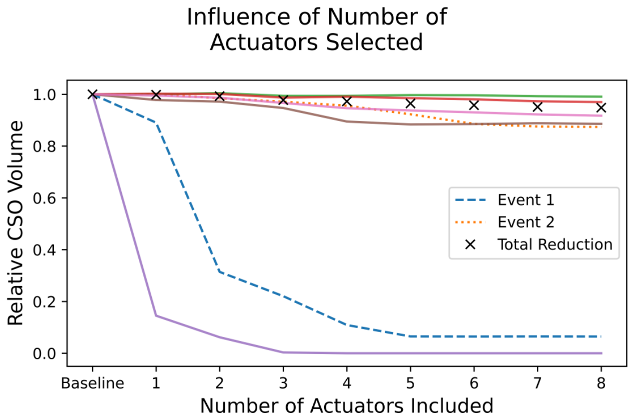


Figure 5.7: Overview of the difference between the four RTC procedures regarding the total CSO. No significant differences between the various options were found, likely attributable to the low number of samples generated.

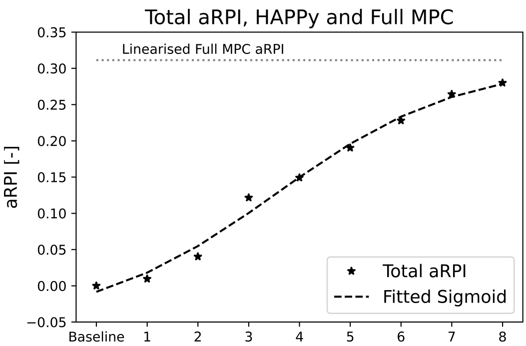
5.2.4. LARGE CATCHMENT – WWTP DOKHAVEN

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 optimisation procedure. The retrained RFs, to predict the specified number of actuators, had no statistically significant difference in the performance compared to those reported in the previous section (Table 5.2). For each of the seven events (see Appendix B Table B.1 for the rainfall event characteristics) the performance is compared to the baseline heuristic control procedure and a fully linearised 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 5.8). 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 0.9-100% for different events. This large range in a relative reduction of CSO volume comes from the relatively large spatial spread of total rainfall depth and maximum rainfall intensity found in the analysed events, impacting the RTC potential.



(a)



(b)

Figure 5.8: (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 analysed below, and the rest 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 linearised MPC, showing the proximity of the 8 actuator HAPPy results.

A maximum total aRPI of 0.28 was achieved when 8 actuators were used in the HAPPy procedure. Although the influence of the number of actuators used in the optimisation problem differs for events (Figure 5.8), 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 the 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 full linearised MPC procedure, the convergence of the HAPPy procedure towards the performance of the full MPC procedure can be observed (see Figure 5.8), but remaining below the achieved performance of the full MPC procedure (with a total aRPI of 0.31 for the events). The additional uncertainties, for this case study, introduced by the further linearisation, 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 linearised model and the model used to represent the physical UDS (a simplified model following the linked dynamic reservoir model). 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 linearised 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 a Kolmogorov-Smirnov two-sample test), but the number of events analysed likely accounts for this.

It should be noted, however, that both the investigated domain and the number of rainfall events are too few to draw statistically significant conclusions about the underlying relation between the number of actuators and the HAPPy procedure performance. Still, after the maximum reduction potential through the HAPPy procedure has been achieved, it is likely that the increase in actuators negatively impacts the UDS performance for the HAPPy procedure: as more actuators are included, the depth of the search, limited by the used sampling interval, and potential for convergence can decrease leading to sub-optimal results in terms of the objective function (weighted CSO volumes) 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 optimisation) was still below the sampling interval for all runs performed across events (see Appendix B Figure B.1), 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 optimisation problem, the algorithm can reduce the complexity to allow for non-linear models to be optimised in real-time without significant uncertainties introduced in the internal-MPC model.

Aside from the difference in (realised) 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 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 5.4). 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 towards the urban canals, as specified by the optimisation objective function (see Chapter 3).

The other two events (events 1 and 5) have two main characteristics in common: (a)

Table 5.4: 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.

Event	**Percent change in total CSO volume reduction per actuator interval**							
	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	0.0	12.1	10.6	12.1	26.4	29.3	8.1	1.3
#3	0.0	-45.3*	**110.1***	1.1	-32.4*	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	6.10	10.2	24.3	24.6	10.5	8.9	9.7	5.8

* Due to the relative loss in total CSO volume reduction at the 1-2 and 4-5 interval, 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.

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a large distribution in the standardised rainfall (standardised 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 grey boxes in Figure 5.9). The former indicates the presence of a breaking point for events that have the highest potential for improvement through RTC (Vezzaro, 2022). The combination of spatial heterogeneity and relative low total rainfall depth in the events lead 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 analysed 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 8. These two are represented by the dashed and dotted lines in Figure 5.8 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

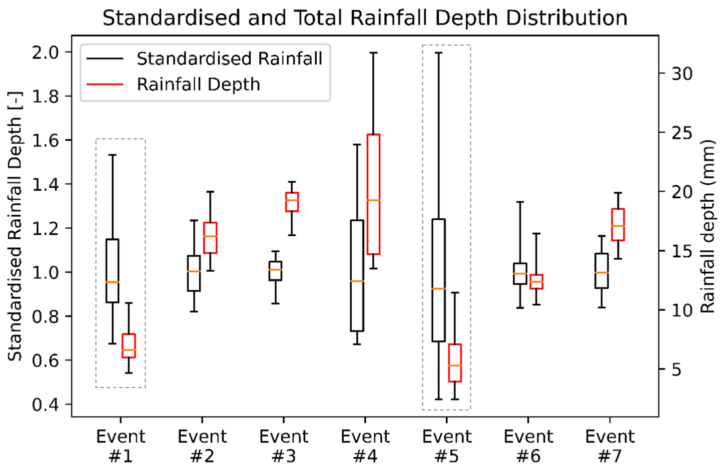
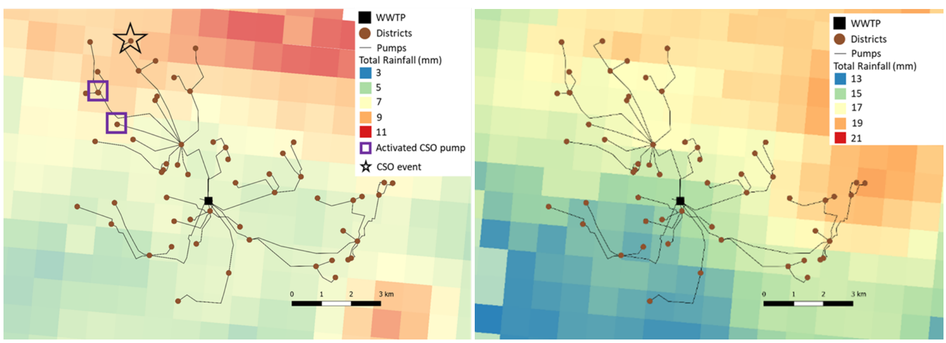


Figure 5.9: Standardised and total rainfall depth distributions of the rainfall over the WWTP Dokhaven UDS. The distributions highlighted by the dashed grey boxes are the events categorised as including a breaking point. Whiskers indicate the full range of observations during the event.

and optimisation procedure are examined in further detail.



(a) (b)

Figure 5.10: Overview of the spatial distribution of the total rainfall (in mm) of the two analysed 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 colour changes between the events.

5.2.5. ANALYSIS OF EVENT 1

The first event is a highly heterogeneous rainfall event, with rainfall depths exceeding the static capacity recorded only around the north-western section of the UDS (see Figure 5.10a), where the other parts received only between 4 and 7 mm over a 36 hour period (during a single peak with a mean duration of 3.3hrs). The total CSO volume of 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 black star in Figure 5.10a, 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:

$$PCSO_4 \wedge PCSO_{12} = \begin{cases} 1, & if\, FD_3 \geq 0.8 \mid FD_4 \geq 0.8 \mid FD_{12} \geq 0.8 \\ 0, & \text{otherwise} \end{cases} \tag{5.4}$$

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:

$$P_{4\to3} \wedge P_{12\to3} = \begin{cases} 0, & if\, FD_3 \geq 0.8 \mid FD_4 \geq 0.8 \mid FD_{12} \geq 0.8 \\ 1, & otherwise \end{cases} \tag{5.5}$$

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 45min at district 12 (Figure B.2a), 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 Appendix B Section B.3 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 Figure B.2-B.4). 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 5.8(a)). No additional CSO volume reduction was observed for the inclusion of more actuators, but no performance drop was observed either. The linearised MPC showed behaviour that is similar to that observed when more than five actuators were used in the HAPPy procedure.

Although the synergy between the real-time optimisation and the heuristic part of the HAPPy procedure managed to negate the pumped CSO event, it required the selection of 5 actuators for optimisation, 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 optimised in real-time, able to more effectively synergise between real-time optimisation and heuristic procedures.

5.2.6. 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 5.10b). 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 5.11). This changing of the most relevant actuators led to frequent changes in the pump settings, a UDS behaviour that is often undesirable and optimised against in an RTC context (Mounce et al., 2019; Sun et al., 2020b). 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 behaviour through the selection of the actuators or by including a set-point change penalty within the optimisation function. The development of these safeguards, however, is deemed outside the scope of this work.

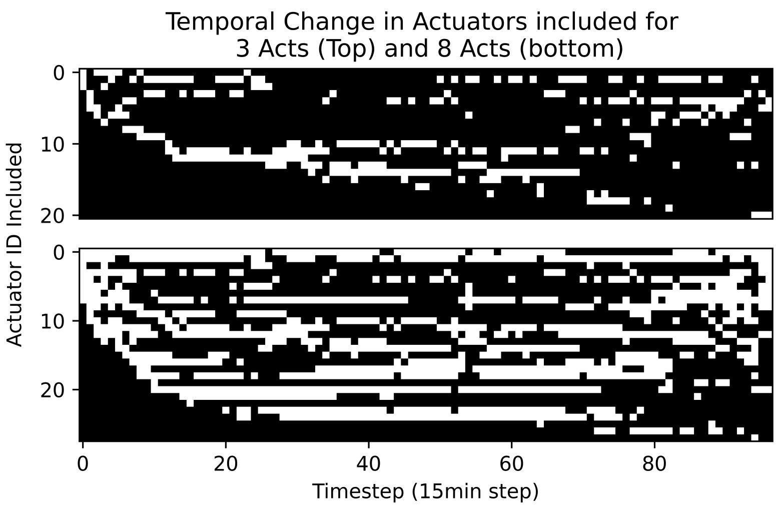


Figure 5.11: Temporal changes on the actuator IDs which are included in the HAPPy procedure (indicated by white) for the run with the three actuators included (top figure) and eight actuators (bottom figure).

Local CSO reductions were especially pronounced when multiple actuators affecting the same part of a cascade were selected in the optimisation procedure also visible in the continuous improvement when multiple actuators are included. Utilising 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 suggests a high level of case-study and rainfall dynamic specificity. The ability of the HAPPy to optimise 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.

5.3. CONCLUSIONS AND FUTURE OUTLOOK

This chapter proposes a new heuristic and predictive policy (HAPPy) for the near-optimal real-time control (RTC) of large urban drainage systems. The HAPPy utilises a set of offline determined characteristics to optimise the subsection of an urban drainage system (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 optimising 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 model predictive control-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 real-time control 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 optimisation search space by selecting which actuator should be included in the optimisation 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 heavier rainfall events 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 rainfall events with high total depths,

however, was more spurious, leading to potentially undesirable frequent changes in the settings of the actuators during the optimisation.

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. This work aimed at developing the procedure, aiming to reduce model uncertainties due to reducing the linearisation needs. However, the double reliance on rainfall forecasts within the HAPPy procedure might 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 optimisation are other aspects that should be explicitly understood.

As the work here highlights the ability of MPC to co-optimise with heuristic control, the ability to optimise parts of the UDS during failure events could be an effective procedure when partially based on the HAPPy procedure, Work investigating how to implement a HAPPy-based fail-safe would be required. Further optimisation 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 and local real-time control procedures would also give a better insight into the potential use of the proposed methodology.

6

Risks Associated with Uncertainties in Model Predictive Control

Real-time control strategies can, as mentioned before, either be based on heuristic or optimisation-based algorithms. Optimisation-based algorithms commonly use models to predict the optimal settings for a system over a receding horizon in the form of Model Predictive Control (MPC) and show greater theoretical potential to optimise the CSS operation with regard to the set objective compared to heuristic algorithms (Lund et al., 2018). In MPC strategies real-time measurements of the system are used as initial conditions for an internal MPC model, precipitation forecasts as a forcing variable and pumping capacities as model parameters. The objective of the RTC can take many forms but typically aims to minimise environmental impact directly (impact-based RTC) and reduce the pollution loads from the CSS (pollution-based RTC) or the volume of CSO discharge (volume-based RTC).

In modelling studies, used to assert the performance of an MPC strategy prior to implementation, various sources of uncertainties which can impact the expected MPC performance are inherently introduced in the process. Uncertainties related to model parameters and precipitation forecast on model outputs have been studied (e.g. Achleitner et al. (2009) and Deletic et al. (2012)) but the influence of these model uncertainties on the performance potential of RTC strategies have not explicitly been considered (Lund et al., 2020). Normally, the internal MPC model is often used as the model representing the system, thus negating any uncertainties that might occur (e.g. Sadler et al. (2019) and Sun et al. (2020b)). Considering precipitation forecast, several methods to account for precipitation uncertainty in an RTC setting have been proposed (Courdent et al., 2015; Svensen et al., 2021). Additionally, it has been argued that the precipitation uncertainty will not influence the final MPC performance significantly due to the re-updating of the initial conditions at every optimisation interval (Fiorelli et al., 2013).

Similar results were shown in other research, though the performance decreases (difference between the theoretical and uncertain data use), as shown in Table 6.1, vary widely, from almost negligible to almost half of the gained performance. From these

This chapter is an adapted version of: van der Werf, J.A., Kapelan, Z. and Langeveld, J. (2023). Real-Time Control of Combined Sewer Systems: Risks Associated with Uncertainties. *Journal of Hydrology*, **617**A, 128900, doi: 10.1016/j.jhydrol.2022.128900

Table 6.1: Overview of the current literature assessing the functioning of various real-time optimisation procedures under uncertainty. Two types of control procedures have been reported on: Deep Reinforcement Learning (DRL) and Model Predictive Control (MPC). The performance loss (perf. loss) referred to in the table is caused by the uncertainties induced in the MPC procedure

Control Procedure	**Uncertain parameter**	**Synthetic/Real**	**Perf. loss**	**Reference**
DRL	Monitoring values	Synthetic $U(0.75, 1.25)$	59%	Zhang et al. (2022)
DRL	Rainfall forecast	Synthetic $U(0.95, 1.05)$	1.6%	Saliba et al. (2020)
MPC	Rainfall forecast	Synthetic (constant)	1.2%	Fiorelli et al. (2013)
MPC	Rainfall forecast	Real	344%	Raso et al. (2014)*
MPC	Rainfall forecast	Real	37%	Jafari et al. (2020)
MPC	Runoff	Synthetic (-20%)	2.8%	Svensen et al. (2021)

*These results pertain to the real-time optimisation of a reservoir rather than a UDS, with different dynamics and a longer forecast horizon used.

publications, which use both MPC and Deep Reinforcement Learning (DRL), no clear trends in performance loss could be established. Despite the many uncertainties potentially influencing the efficacy of RTC procedures highlighted, the main source of uncertainty assessed remains rainfall forecast/nowcast (Table 6.1, also see Lund et al. (2018)). Assessing the influence of this source of uncertainty seems to depend on how the uncertainty is modelled, as the use of real cases and large biases seem to exacerbate performance loss. Research on multiple (simultaneously modelled) sources of uncertainty, however, is limited to synthetically added noise to input data (thereby arguing the various uncertainties are compiled into a single uncertainty). Additionally, the use of real data to accurately represent the dynamics of uncertainty in a UDS context remains limited. Although both methods have merit in the development of new, more robust control measures (e.g. Svensen et al. (2021)), it does not further the understanding of the relation between uncertainties and RTC efficacy nor enable further targeted research.

Furthermore, during the operation of a CSS, changes to the system's dynamic capacity can occur as a result of pump failure, emergency or scheduled maintenance at the WWTP or pumping stations and other unforeseen events such as (partial) blockages. Failure events related to actuators show the highest level of risk within urban drainage systems (Miszta-Kruk, 2016). These temporary changes to the system capacity occur frequently in CSS and can exacerbate CSO volumes significantly in practice (Korving et al.,

2006) for uncontrolled systems. As RTC strategies are designed to fully utilise the redundancy of the CSS capacity, the effects of these system capacity uncertainties on the system functioning are an important interaction to understand. RTC algorithms able to maintain functioning during failure operations, so-called *fault-tolerant control*, either focus on failures in the information streams (Garofalo et al., 2017), or theoretical, local actuator failures (Ocampo-Martinez & Puig, 2009) and return to the 'pre-RTC' state when failures are detected (Pleau et al., 2005). The cumulative effect of the aforementioned uncertainties and failure mechanisms on the efficacy of an RTC strategy has not been studied before and was identified as a key gap in the RTC literature (Chapter 2).

Additionally, the uncertain nature of the practical efficacy of RTC to improve stormwater system performance remains one of the main concerns of practitioners (Naughton et al., 2021) and it can be assumed that these concerns apply to combined sewer system RTC as well. This results in limited practical applications of MPC (Lund et al., 2018). Research assessing the risks of practical operational uncertainties on MPC efficacy is needed to ensure more widespread implementation of the technology. The key novelty of this work will be to assess the relative importance of various sources of uncertainty (model-induced, rainfall and system capacity uncertainties) using real operational and forecast data. In this chapter, the aim is to develop a methodology which systematically assesses the influence of different sources of uncertainty on the performance of model predictive control procedures and to quantify the influence of these sources of uncertainty on the MPC performance. This is done through the application of an MPC procedure to the case study of Eindhoven (see Chapter 3.2 for more details).

6.1. METHODOLOGY

The developed methodology aims to assess the risks of different uncertainties on the performance potential of an MPC scheme. These are computed based on a standardised methodology using the model-based performance of the RTC strategy under different scenarios with varying levels of uncertainty considered. First, an MPC architecture based on an optimisation model is set up and the sources of uncertainty within the architecture are determined (section 6.1.1). Then, based on the identified sources of uncertainty, scenarios are defined (section 6.1.2) and these scenarios are evaluated using a risk-based assessment methodology (section 6.1.3). If risks are identified, the underlying mechanisms are investigated. To illustrate the application of the methodology and to assess their influence on the relevant risks the case study of Eindhoven (see Chapter 3 for the catchment details) is used and the applied control procedure is set out in Section 6.1.4.

6.1.1. MODEL PREDICTIVE CONTROL ARCHITECTURE

A centralised MPC architecture is developed using the full-hydrodynamic model of Riool-Zuid to represent the physical combined sewer system. The conceptual model based on the full-hydrodynamic model was created for optimisation purposes hereafter denoted as the internal MPC model following the definition by Lund et al. (2018) (see Chapter

3.2 for the calibration and development of this model). The centralised MPC architecture follows the procedure outlined in Figure 6.1. The full-hydrodynamic model is used to assess if there is a need for an optimisation run: optimisation will only be done during conditions or predicted conditions within the forecast horizon that fall within the optimisation objective. Several sources of uncertainty exist in real MPC affecting the final optimal actuator settings (Figure 6.1, data and processes indicated with dashed lines represent various sources of uncertainties considered in this work).

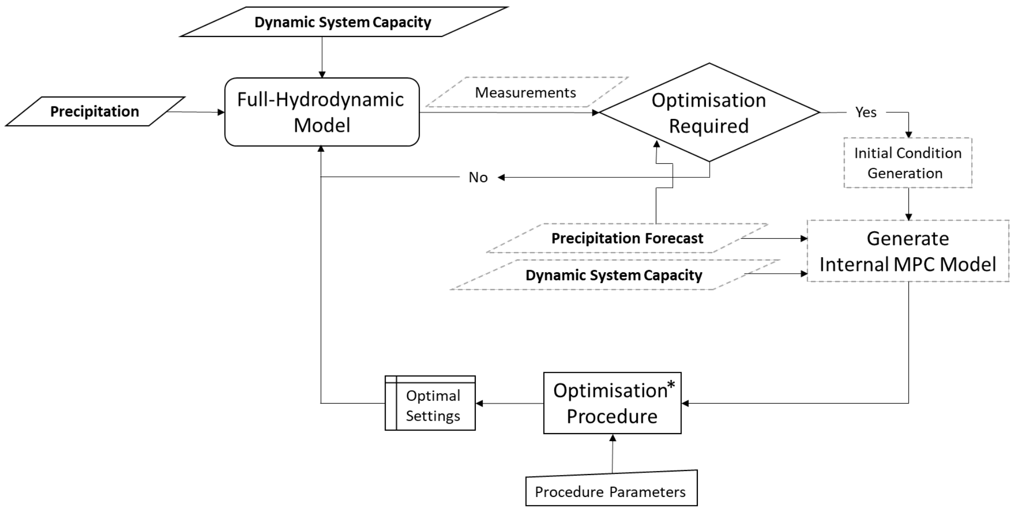


Figure 6.1: MPC Scheme followed for every time step. Dashed lines indicate uncertain processes within the MPC scheme.*Optimisation procedure follows the method set out by Sadler et al. (2019)

The generation of the internal MPC model requires initial conditions regarding both the runoff and the flow routing model, precipitation forcing data, actuator capacity conditions and model structure calibrated previously. Initial conditions for the internal MPC model are the hydraulic heads of the UDS sections, flow rates between the UDS sections, infiltration and initial loss parameters are derived from the full-hydrodynamic model. The runoff initial condition is estimated using a warm-up period of two hours for every time interval.

The dynamic system capacity of a combined sewer system refers to the wastewater treatment plant capacity and/or any intermediate pumping station capacity, in this case, the pumping station Aalst is the downstream boundary condition and therefore dynamic system capacity. Both suffer from variable flow rates due to planned and unplanned activities in the system. The full-hydrodynamic model upper bound for these actuators (the theoretical capacity) is replaced by dynamic boundary conditions based on historical operation observations. This mimics the observed, i.e. actual operational capacity available during the event. The precipitation forecast parsed to the internal MPC model is either the observed precipitation representing a perfect forecast (e.g. Zimmer et al. (2015)) or the actual, i.e. real historical forecasts (Löwe et al., 2016).

Table 6.2: Overview of the relevant uncertainties potentially impacting the performance of the MPC system

Variable	Perfect information case	Uncertain/Real case
Simplified model	Perfect Digital Twin of the drainage network as the internal MPC model	Simplified Model Structure as the internal MPC model
Initial Conditions	Copy of the last conditions in the optimisation framework	Sensor output and interpolation
Precipitation Forecast	Forecasted precipitation is the same as occurred	Meteorological Model output
Dynamic Boundary Condition	Perfect knowledge of the future behaviour	Assumed constant as pre-defined set point
Actuator Functioning	Actuator behaves as determined by the centralised controller	Observed occurrence of blocking or missed signals

6.1.2. UNCERTAINTY SCENARIOS

To understand the influence of the previously highlighted uncertainties in the system, a generic methodology was set up. This methodology is set up such that all relevant uncertainties potentially affecting the MPC performance can be integrated and combined. A scenario-based approach, varying the uncertainties within the MPC architecture, was used to assess the influence of different variables on the performance of the MPC procedure.

The influence of the aforementioned sources of uncertainty can be determined stochastically and deterministically. Following a stochastic framework, random or semi-random errors can be introduced to the variables in order to generate uncertain scenarios. However, the number of samples which can be used is limited given the real-time optimisation needs for MPC, making a stochastic framework impractical. A deterministic approach to uncertainty assessment involves defining a 'perfect information' and 'uncertain/real' case per variable, based on real data. The perfect information scenario refers to the scenario where the information parsed to the internal MPC model is entirely the same as the state of the UDS (or full-hydrodynamic model of the UDS), whereas the uncertain/real scenario refers to the scenario which would be the case for the implementation of MPC in a real system, using the real data. A deterministic approach was used in this research as it better represents the real uncertainties that occur within an MPC framework and it can give meaningful results without the computational burden of a stochastic approach. Details for both the cases per previously identified variable (Figure 6.1) can be found in Table 6.2.

Three of the aforementioned variables require operational data: (1) Initial conditions

Table 6.3: Overview of used scenario pertaining to the information parsed to the internal MPC model of the Riool-Zuid model

Scenario	**Perfect information variables**	**Uncertain variables**
Scenario 1 – Perfect Baseline	Simplified Model, Initial Conditions, Precipitation Forecast, Dynamic Boundary Condition, Actuator Functioning	None
Scenario 2 – Practical Baseline	Initial Conditions, Precipitation Forecast, Dynamic Boundary Condition, Actuator Functioning	Simplified Model
Scenario 3	Initial Conditions, Precipitation Forecast, Actuator Functioning	Simplified Model, Dynamic Boundary Condition
Scenario 4	Initial Conditions, Dynamic Boundary Condition, Actuator Functioning	Simplified Model, Precipitation Forecast
Scenario 5	Initial Conditions, Actuator Functioning	Simplified Model, Precipitation Forecast, Dynamic Boundary Condition

requires an operational understanding of the sensor output, (2) dynamic boundary condition uses observations of the functioning of the dynamic boundary condition (monitored pumping station capacity or WWTP capacity) and (3) the actuator functioning requires the reconstruction of previous set points and the comparison with the resultant set point for each actuator. There could be an overlap between the latter two if the pumping stations or WWTP are part of the control strategy. The other two (simplified model and precipitation forecast) both rely on model outputs only and therefore do require the operation of the CSS for data generation.

The influence of the three sources of uncertainty for the internal MPC model mentioned in Section 6.1.1 were investigated in this paper: (1) simplification of the internal MPC-model, (2) precipitation forecast and (3) the dynamic boundary condition. These three were selected as data was available for the uncertain/real, as the other two require implementation of the studied control algorithm for data, which has not been implemented yet. Based on these three sources of uncertainty, five scenarios were defined, combining different sources of uncertainty with the internal MPC procedure (Table 6.3).

The computational penalty associated with MPC implementations is always limiting to the number of events that can be studied, which should be considered when interpreting the results, as multi-year simulations are necessary for an accurate assessment of the performance of RTC strategies (van Daal et al., 2017). The computational time for Scenario 1 is especially high (a six-hour rain event takes over 20 days to simulate), as the full hydrodynamic model is used as the internal MPC model, limiting the number of events that can be studied further.

6.1.3. RISK AND PERFORMANCE ASSESSMENTS

To quantify the risks associated with implementing RTC we define two risks: (1) the risk of relative system performance loss and (2) the risk of operative deterioration. The risk of relative performance loss quantifies the difference between the theoretical and real MPC performance based on aforementioned uncertainties in the RTC design process (represented here using the five scenarios shown in Table 6.3) on observation data. The risk of operative deterioration is defined as the risk of operation of the sewer system using RTC that is worse than the static optimal operation (defined as having a single set-point for each actuator in the CSS).

To gain an objective insight into the functioning of an RTC system, the absolute Realised Potential Indicator (aRPI) was previously introduced (see Chapter 4). First, the total aRPI and aRPIs per event are calculated for scenario 1 (i.e. the baseline scenario). These form the theoretically achievable potential of the MPC strategy. Then the total aRPI and aRPI per event are calculated for the other three remaining scenarios outlined in Table 6.3. The difference between the total aRPI for a given scenario and the total aRPI for the baseline scenario (i.e. scenario 1) is used as the final indicator of the risk of relative performance loss. The corresponding distributions of the aRPI are also assessed to see if there is a statistically significant difference between the scenarios, using the Kolmogorov-Smirnov test (KS-test). If there is a significant difference between the scenarios, the dynamics in the system causing the difference are further investigated. If this is not the case, the source or set of sources of uncertainty is deemed to not have a significant effect on the performance of the MPC procedure. Additionally, a relation of the risk of relative performance loss per event to precipitation and system capacity characteristics is then assessed by analysing the total rainfall depth, maximum rainfall intensity and median system capacity during wet weather flow operation.

The risk of operative deterioration does not compare to the perfect baseline (Scenario 1) but rather uses the statically optimised RTC results (the baseline of the RPI) as the baseline. This risk is defined as the frequency of controlled events which perform worse compared to the static optimal performance. The magnitude of the deterioration is accounted for in the risk of relative performance loss and is therefore not part of the risk of operative deterioration. The risks as described here can be used for a more informed risk/benefit analysis, to allow for a more rational implementation of RTC in practice.

6.1.4. CONTROL PROCEDURE

A volume-based RTC strategy was selected and applied to the Eindhoven Case study to minimise additional uncertainties inherent in models required for pollution- and impact-based RTC. Volume-based RTC remains a popular objective in the scientific literature and practice due to alignment with monitoring and regulations (Meng et al., 2020). To optimise the actuators at every time step following the used architecture (Section 6.1.1) a general objective function was formulated. The objective function used in this control procedure is based on the following three functions: (1) flooding minimisation, (2) CSO volume minimisation and (3) equal filling degree (Equations 6.1, 6.2 and 6.3 respectively) following previously defined optimisation functions (Fiorelli et al., 2013; Gelormino & Ricker, 1994; Pleau et al., 1996). The objective functions are defined as follows:

$$\boldsymbol{J}_{flooding}(T) = \Delta t \sum_{i=1}^{n_{nodes}} q^i_{flood} \tag{6.1}$$

where Δt is the time step length of each iteration, n_{nodes} is the number of nodes in the model and q^i_{flood} is the flooding rate for the i$^{\text{th}}$ node in the model.

$$\boldsymbol{J}_{cso}(T) = \Delta t \sum_{i=1}^{n_{cso}} q^i_{cso} \tag{6.2}$$

6

where n_{cso} is the number of CSO structure in the system and q^i_{cso} is the overflow rate for the i$^{\text{th}}$ CSO structure. Each CSO structure could be assigned a weight (e.g. Vezzaro and Grum (2014)), but here the relative importance of each CSO was deemed equal.

$$\boldsymbol{J}_{filling\ degree}(T) = \sqrt{\frac{\sum_{i=1}^{n_{sections}} (fd_i - \mu)}{n_{sections}}} \tag{6.3}$$

where $n_{sections}$ is the number of controlled UDS sections, fd_i is the i$^{\text{th}}$ filling degree in the system and μ is the mean filling degree over all the sections.

The three objectives are combined to form a single objective function following:

$$minimise\ a_1 * \boldsymbol{J}_{flooding} + a_2 * \boldsymbol{J}_{CSO} + a_3 * \boldsymbol{J}_{filling\ degree} \tag{6.4}$$

where a_1, a_2 and a_3 are weights used to discern the importance of each term, here set to 10,000, 100 and 1 respectively. These weights were chosen to ensure clear prioritisation of flooding over CSO events, as within a GA framework these cannot be added as hard constraints. Note that the third term in Equation 6.4 was added to the optimisation objective to include equal filling of the system, even when CSOs are not predicted and thereby reducing the risk of overflows occurring beyond the forecast horizon.

The optimisation function is subject to implicit constraints (mass and energy balance equations implemented in EPA SWMM5). To minimise undesired erratic actuator movement, the change in set point at every time step was explicitly constrained to a maximum change of 300 m3/h per time step. This explicit constraint was added to avoid the need to add another objective to the objective function, as done in Sun et al. (2020b).

The above optimisation problem was applied to the simplified model of case study Eindhoven, highlighted in Section 3.2, is solved using a conventional elitist Genetic Algorithm (Goldberg, 2013), as it is commonly applied in water resource management (Nicklow et al., 2010) and urban drainage system modelling, with RTC in particular, for many years (Rauch & Harremoës, 1999). The calculated set-points are the flow rate restriction at the two control stations, with the first of each being implemented after optimisation. Given the non-linear dynamics in the model, formal optimisation using linear or quadratic programming could not be applied without increasing the level of uncertainty in the internal-MPC model. In this case study, this is done every 5 minutes of simulation time, over an RTC forecasting horizon of 2 hours. A GA population size of 20, mutation probability of 0.1 using a uniform mutation operation, crossover probability of 0.5 for uniform crossover operation, a parent portion of 0.25 and a rank-based selection operator were used. These parameters were iteratively chosen to ensure good search performance. The MPC scheme was run locally on a desktop with a four-core Intel i5-6500 CPU @ 3.20 GHz CPU. As a baseline (the single-input, single-output heuristic control), the results presented in Chapter 4 are used with set-points of $5,000 m^3/h$ and $2,500 m^3/h$ for CS De Meeren and CS Valkenswaard respectively.

For the catchment, flooding issues do not occur frequently due to a CSO capacity of around 20 mm/hr. The inclusion of the flooding term in the objective function (equation 6.1) therefore did not affect the actuator settings for the used catchment, but was included to follow a more generalised approach to MPC to facilitate and formalise result comparisons.

6

6.1.5. RAINFALL EVENTS USED

Two types of precipitation data were used in this case study: (1) the rain-gauge adjusted radar dataset (Overeem et al., 2009) and (2) the radar precipitation prediction made by the Royal Netherlands Meteorological Institute (KNMI), based on two real-time radar reflectivity measurements and advective velocity extrapolation of previous observations. The latter is available in real-time and can be used in predictive control, where the former is adjusted based on the merging of national and international radar data with the KNMI-operated rain gauge network, available with a delay of a month. Both datasets have a resolution of 1x1 km at a 5 min interval and 128 pixels were used in the EPA SWMM5 model, corresponding with the Eindhoven case study area. Radar reflectivity for the prediction data is converted to precipitation depth using the following empirically derived equation (Marshall et al., 1955):

$$I = 10^{\frac{Z-109}{32}} * \Delta t^{-1} \tag{6.5}$$

where I is the precipitation intensity in mm/hr, Z is the reflective factor observed in dBZ and Δt is the observation time step.

The historical prediction data set used here spans the years 2014 and 2015. Precipitation events within these two years were selected. Usable events were defined as precipitation events resulting in wet weather flow throughout at least 2 UDS sections of Riool-Zuid, with data available for pumping station Aalst. The latter requirement was only met for the 2015 data set. A total of 17 precipitation events from 2015 were used in the final analysis for scenarios 2 to 5. This includes 'hybrid-events', i.e. events with various rainfall peaks considered as one event. The maximum intensities for the events ranged from $2.17-30.58mm/hr$ (mean of $10.74mm/hr$) and depths ranging from $6.2-43.5mm$ (mean of $18.3mm$). Two rainfall events were used for assessing scenario 1, with maximum intensities of 13.0 and $10.75mm/hr$, and total rainfall depths of 28.7 and $14.3mm$ for events 1 and 2 respectively.

6.2. RESULTS

This section shows and discusses the results obtained from the simulations as described in the previous section. Firstly, the risk of relative performance loss is shown, followed by the risk of operative deterioration. The former is assessed for the difference between Scenario 1 and 2, followed by the other three scenarios.

6.2.1. RISK OF RELATIVE PERFORMANCE LOSS

Scenario 1 can be seen as the highest possible achievable MPC performance for the used strategy and procedure, as it neglects all forms of uncertainty which might affect the performance (named here the theoretical functioning). Scenario 1 performed better for the events with a total aRPI of 0.79, compared to 0.50 for Scenario 2 (Table 6.4, Figure 6.2), indicating both considerably improved the system functioning and relative proximity to the maximum achievable performance. Compared to the baseline, this represents a CSO reduction of 68.7% and 44.4% respectively. This equates to a 35% relative loss, based on model uncertainty alone.

Table 6.4: Difference between Scenario 1 and 2

Scenario	**aRPI [-]**	**CSO Reduction compared to baseline [%]**	**Relative Loss Compared to Scenario 1 [%]**
Scenario 1	0.79	68.7%	-
Scenario 2	0.50	44.4 %	35 %

This difference was assessed by looking at the behaviour of the most downstream actuator in the system, which was noticeably different during the CSO events. During the phase of the event when the CSO occurred, in Scenario 1, the flow through Actuator 1 was restricted further compared to Scenario 2, reducing the CSO volume at the downstream locations (Figure 6.2). This did cause a limited increase in the CSO rate at the upstream CSO, such that the total CSO volume was minimised. In Scenario 2, more flow was allowed through this control station, causing an overall increase in the CSO volume

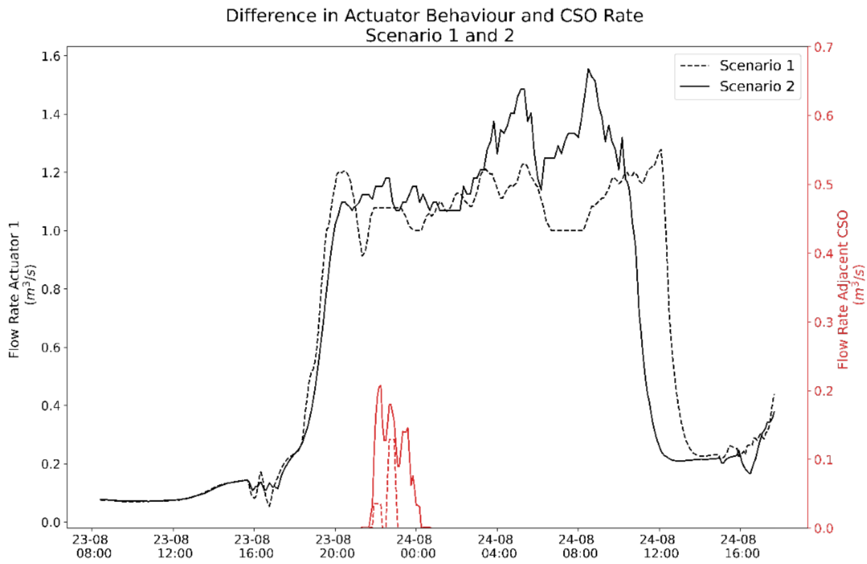
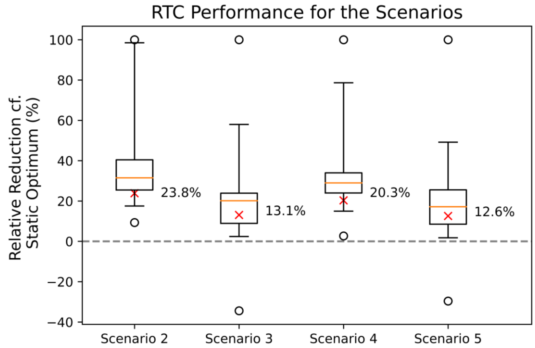


Figure 6.2: Example of the difference in actuator behaviour between Scenarios 1 and 2.

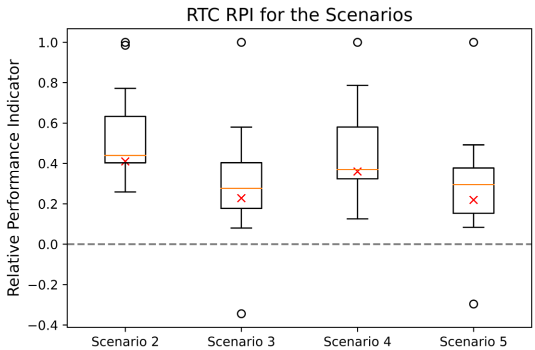
As Scenario 1 (the perfect baseline) could only be analysed for two events, Scenario 2 (the practical baseline) was used as the baseline for showing the maximum achievable potential of the used MPC scheme. The total CSO volume of Scenarios 2 till 5, following the MPC strategy set out in Section 6.1.4, were compared to the total CSO volume obtained using the static optimum settings as determined in previous work (Chapter 4). Reductions in the total CSO volumes of the 17 analysed precipitation events were found for all four scenarios (Figure 6.3i and ii). The box plots (whiskers indicating the 5-95% CI) were constructed based on 12 events, as five of the used events did not cause overflows in the static optimum.

Scenario 2 showed, for the 17 analysed events, a 23.8% reduction in the total CSO volume and the negation of CSO events for two additional precipitation events. The absolute RPI for the combined events is 0.53. The latter value indicates the existence of unutilised potential within the system, although unlikely to be achieved through RTC with the current actuator configuration. For two events, the MPC scheme managed to negate the CSO event entirely.

A relatively small relative performance risk was observed for Scenario 4 (using real radar forecast data in the optimisation model), with an aRPI of 0.46 and CSO reduction of 20.3% compared to the baseline, equating to a 14.4% performance loss compared to Scenario 2 (Table 6.5). One CSO event was negated for Scenario 3, one less compared to Scenario 2. This suggests only a limited risk of relative performance loss when using radar forecasts. The frequent updating of the internal MPC model ensures that the



(a)



(b)

Figure 6.3: (a) Relative Improvement of the RTC per scenario. (b) the RPI difference per scenario

importance of accurate forecasting is minimal. Recent advances in precipitation forecasting are therefore unlikely to yield higher practical performance from MPC systems. Longer horizons and application of precipitation forecasts to heuristic control have not been assessed in this work and might show different performance-related risks.

A more pronounced relative performance risk was associated with assuming the full capacity of the downstream pumping station, with a relative reduction of 45.2% and 47.3% for Scenarios 3 and 5 respectively. Both scenarios exacerbated the frequency of the CSO events, with an increase in the number of events with CSO spills. The relatively large loss of performance corroborates findings by Sun et al. (2020a), which indicate a decrease in efficacy of the MPC scheme under variable WWTP capacity. They, however, consider their variable capacity as a process which can be modelled, whereas the pumping capacity decrease here is considered aleatoric in nature.

The uncertain precipitation forecast and pumping capacity together do not synergistically influence the performance of the MPC scheme in a significant manner based on these results. Indeed, the mean and median of the performance difference between Scenario 3 and 5 for these 14 events were 0.5% and 0% respectively. Assessing the statisti-

Table 6.5: Overview of the performance and performance loss per scenario

Scenario	**aRPI [-]**	**CSO volume reduction [%]**	**Number of CSO events negated [-]**	**Relative Loss Compared to Scenario 2 [%]**
Scenario 2	0.53	23.8%	2	-
Scenario 3	0.29	13.1%	-2	45.2%
Scenario 4	0.46	20.3%	1	14.4%
Scenario 5	0.28	12.6%	-1	47.3%

cal significance of the difference in performance, only the difference between Scenarios 2 and 3 and between Scenarios 2 and 4 were statistically significant (following a KS-test with $p < 0.05$), as indicated by the scatter plots in Figure 6.4 (blue indicating significance, orange a lack thereof).

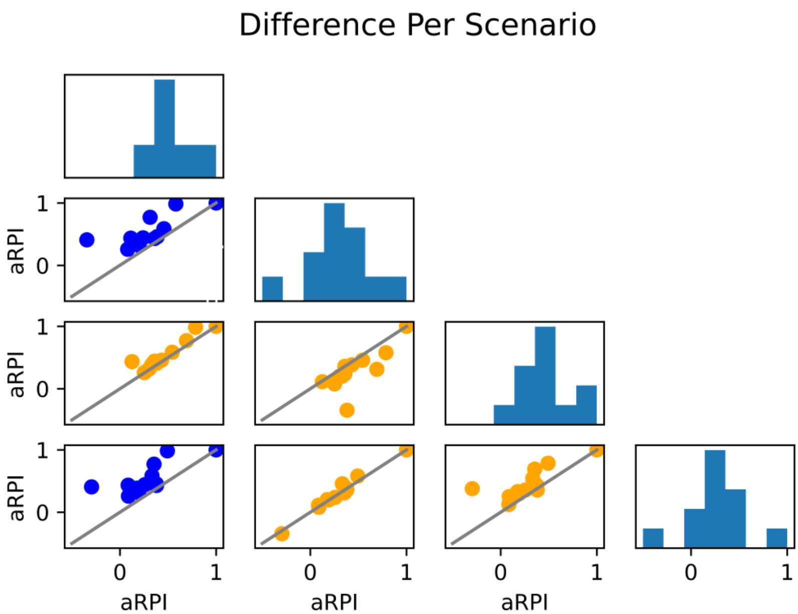


Figure 6.4: Comparison between the Scenarios, blue indicating a statistically significant difference (KS-test, $p < 0.05$)

The relative increase in CSO volume for Scenarios 3 and 5 is associated with an increase in the spill volume of the most downstream CSO structure. As the optimisation-based RTC model assumes full dynamic capacity in the most downstream UDS section of the sewer, it reduces less the flow rate through the control stations causing an accumulation of water in the downstream UDS section and leading to increased CSO volumes. An example of this behaviour is shown in Figure 6.5, at the Control Station De Meeren, the most downstream of the two control stations. For the example in Figure 6.5, Scenario 2 did increase the CSO volume at the upstream CSOs, however, that increase was less compared to the CSO volume it reduced at the downstream most CSO location.

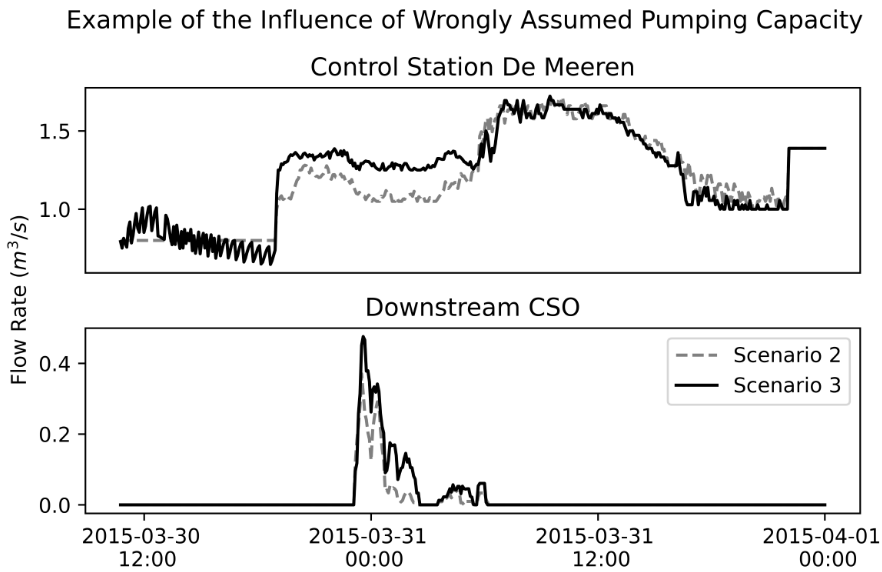


Figure 6.5: Example on the different decision made by the optimiser

A relation between the relative performance loss and precipitation characteristics was investigated too. Total rainfall depth was previously found to be the best indicator of CSO volume for uncontrolled catchments (Fu & Butler, 2012). No such relation could be found from the simulated events presented here (Figures 6.6i-iii). The size of the dataset hampers the ability to draw significant relations within the dataset, for which a larger dataset would be necessary. However, linear correlations between precipitation characteristics and performance loss are not expected, given that such linear relations are not present in RTC performance either (Vezzaro, 2022)

6.2.2. Risk of Operative Deterioration

The risk of operative deterioration was assessed for Scenarios 2-5. Although uncertainties associated with the optimisation model (model parameter, structure and initial condition uncertainties) are present in all scenarios, no operative deterioration was found for Scenarios 2 and 4. However, for both Scenarios 3 and 5, for three and two precipitation events respectively, deterioration compared to the static optimal operation was observed, causing additional overflows and overflow volumes for these events.

The additional overflows occurred at the downstream section of the UDS, caused by the same mechanisms which caused the relative performance loss (Figure 6.5). Although

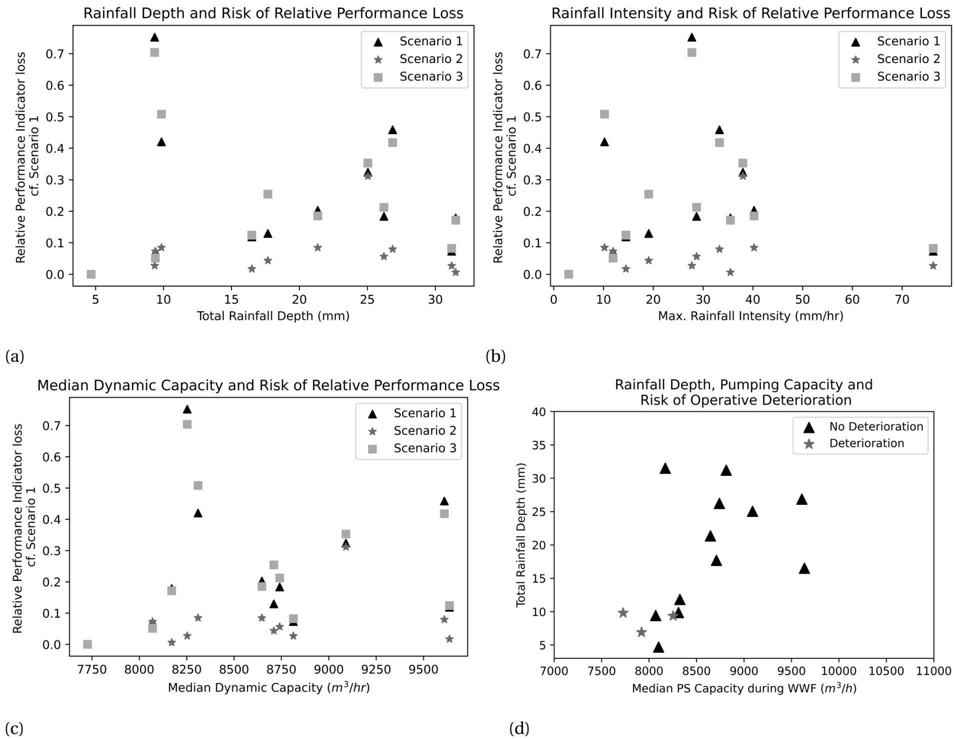


Figure 6.6: (a) Relation between performance loss and total rainfall depth (b) relation between performance loss and maximum rainfall intensity and (c) relation performance loss and median dynamic capacity during wet weather flow. (d) Relation between the rainfall depth, median pumping capacity and operative deterioration for Scenario 2

statistically significant statements cannot be made due to the relatively small sample size, the risk of operative deterioration seems to be the case for the smaller event with a relatively large deviation in performance of the pumping station (Figure 6.6d). This is the type of precipitation event in which RTC typically has the highest potential (Kroll et al., 2018b; Vezzaro & Grum, 2014), which can mean potentially larger risks than reported here given the relatively small dataset within this range of events. Given that an MPC system aims to maximise the system's capacity, uncertainties in the downstream dynamic capacity can have a bigger influence on the system performance if this system is close to its maximum capacity, which is the case for smaller events.

6.3. DISCUSSION

The uncertainty-induced performance loss in this study fall within the range reported in the literature (see Table 6.1). Although the relative performance loss of 14.4% is more significant compared to the lowest bracket found (1.2-2.8%), it is lower compared to the studies using real rainfall forecasts and the highest level of uncertainty (Jafari et al., 2020; Zhang et al., 2022). The latter, using a bias of ±25%, is comparable to the performance loss associated with the reduced pumping capacity (which is in the same range and is also considered a constant bias within the internal-MPC model). This is particularly interesting, as Zhang et al. (2022) used a DRL optimisation procedure, indicating comparable results between different real-time optimisation procedures. It should be noted that the comparison with previously reported values remains difficult due to the case study specificity, relative RTC potential and rainfall events used. Values here are reported in the form of the aRPIs (see Chapter 4), with the aim to allow for better comparative assessment in the future.

The modelling results obtained here show the importance of considering the risks of relative performance loss within the design stage of the MPC strategy. Using this method allows the design of the MPC to be more robust against the perceived risks, and can give operators a more realistic insight into the implementable potential gains of MPC for their respective system. This, in turn, will aid in the decision-making process of investments for future rehabilitation projects of the UDS. Methods to deal with the various sources of uncertainties have been proposed. Lund et al. (2020) proposed a safety margin within their MPC structure of 5%, allowing for random errors within the used model structure. Despite the relatively simple implementation of these safety margins, the robustness against incorrect model parameters was improved without large losses in the theoretical performance of the system.

None of the previous studies reported a risk of operative deterioration within the results. However, often the results shown were compounded in a singular bar chat (as per Jafari et al. (2020)), meaning that a literature comparison regarding the risk of operative deterioration could not be adequately done. As the viability of an MPC strategy, given the risk of operative deterioration, depends on the sensitivity of the receiving water body to CSO discharges, this should be specifically investigated in future, similar research. For highly sensitive receiving water bodies, where the frequency of CSO discharges is the most important parameter, the risks shown here might not be worth the relative benefits. Indeed, frequencies of dissolved oxygen dips and ammonium peaks have been used in the studied catchment before as the optimisable indicator (Weijers et al., 2012). The acceptability of the MPC-associated risks should therefore be dependent on the used assessment framework as described in the Urban Pollution Management Manual 3.1 (FWR, 2018)). Robust risk appreciation frameworks, similar to investment decisions as shown by Sriwastava et al. (2021), should be developed and put in place to enable informed decision-making. Integrated models, able to determine the impact of the CSO events, are necessary to appreciate the risks and benefits for every RTC system. The risks identified here should therefore in future work be extended to impact-based RTC strategies (e.g. Langeveld et al. (2013)).

The risks identified per source of uncertainty should be studied for different catchments to better understand their respective impacts. Additionally, from a practical implementation point of view, various other uncertainties might cause an increase in the risk of operative deterioration (e.g. measurement uncertainty, and communication issues in the RTC strategy). These additional risks should be systematically assessed following the same method as presented here. Although the risks presented here were identified for an optimisation-based control strategy, the same risks can apply to heuristic control measures if not explicitly considered within the strategy.

The relatively large influence of the pumping station-related uncertainty echoes the findings related to the heuristic control procedure developed for the Eindhoven case study in Chapter 4. In the heuristic case, a recalibration of the rules based on the performance of PS Aalst showed to be one of the main ways to improve the heuristic procedure applied to the catchment. Indeed, it was more efficient compared to incorporating nowcast into the operation of the UDS (Santágueda, 2021).

6.4. CONCLUSIONS AND FUTURE OUTLOOK

This chapter proposed a methodology to investigate the potential risks associated with using scenarios with various uncertain variables in a model predictive control (MPC) strategy applied to combined sewer systems (CSSs). Five scenarios were defined to assess the relative impact of the internal MPC-model, dynamic system capacity and precipitation forecast uncertainties. The above risks were assessed in the case study of Eindhoven in the Netherlands.

The following conclusions can be drawn from the case study findings:

- Uncertainties associated with the MPC framework can have a significant influence on the practically achievable performance of the control strategy and should be investigated prior to implementation. Model uncertainties and unanticipated fluctuations in dynamic system capacity were found to have the largest influence on the performance;
- Unanticipated fluctuations in dynamic system capacity can lead to operative deterioration compared to a statically operated system when not considered within the MPC framework;
- Precipitation forecasts uncertainty can cause minor relative performance loss but can be used without significant risk of operative deterioration in an MPC strategy, provided that the optimisation frequency is high enough;
- The sources of uncertainty were not found to synergistically reduce the MPC potential nor increase the risk of operative deterioration;
- The trade-offs between the benefits of an MPC strategy and perceived risks should be explicitly considered before the implementation of MPC strategies.

In future research, additional uncertainties considered outside the scope of this paper should be considered: initial conditions of the runoff and routing internal MPC models and measurement uncertainties, as well as additional combinations of these. Their respective contribution to the here identified risks should be further identified. Furthermore, given the relatively high influence of the internal-MPC model uncertainty on the risks associated with performance loss, a better understanding of the trade-offs between computational speed and accuracy is necessary. A more detailed investigation into the exact mechanics behind the influence of uncertainties should be investigated to facilitate improved risk reduction in future MPC implementations.

Given the large performance loss associated with the system capacity uncertainty and model uncertainty, the development of efficient and robust RTC methods to manage these losses should be prioritised. Additional sources of performance loss, such as the operational performance of actuators, have not been explicitly studied here and should be assessed following a similar framework as proposed here. A comparison between heuristically and optimisation-based controlled system and their respective risks is also recommended. Furthermore, to further validate the results presented here additional simulations are needed on other case studies. The sensitivity of model predictive control to uncertain dynamic capacity should be further assessed for a combined sewer system with multiple pumping stations within the system to further understand the dependency of MPC performance on changing dynamic capacities.

The dynamics between performance loss and rainfall characteristics should be further investigated, as the initial results here show a higher level of risk associated with smaller rainfall events. Smaller rainfall events are found to be more susceptible to improvement through RTC strategies, and the potential impact of these uncertainties on the MPC performance could therefore be higher than described here. These results should therefore have to be validated on additional rainfall events and in other catchments.

This part of the dissertation looked specifically at the influence of various uncertainties on MPC procedures. However, in practice, this type of control has not been applied ubiquitously. Heuristic control procedures, predominately following an optimised form of *rule-based Real-Time Control*, however, can be found in many real UDS. These systems, as shown in Chapter 2, are usually outperformed by MPC systems. Heuristic improvements are therefore needed to bring the operation of UDS closer to a practical optimum. Augmenting rule-based RTC with rainfall forecast might be able to aid in this. However, this means introducing an inherent uncertainty in the operation of heuristic procedures. In the next chapter, the influence of this uncertainty will be assessed in a heuristic setting.

7

Heuristic Control: Risks from Heterogeneous Nowcast Accuracy

Model predictive control was shown, in the previous chapter, to be strongly influenced when considering uncertainties causing an inherent bias in the internal-MPC model. Reducing these uncertainties are therefore a way in which the implementation of MPC procedures can be further promoted. However, the lack of implemented examples and therefore uncertainty about the practical performance of predictive based control procedures remains one of the main barriers against real-time optimisation control implementation (Naughton et al., 2021). Integrating forecasts within existing heuristic control procedures, under the principle of nowcast-informed RTC, could provide the missing link needed towards widespread implementation of more advanced forms of RTC.

Before expanding this form of control with nowcast, the nowcast accuracy and potential associated risks should be considered. Although Chapter 6 showed that short-horizon rainfall prediction, or nowcast, has only a limited influence on the functioning of real-time optimisation procedures, the mechanics ensuring this (the continuous updating of the internal-MPC model) might not be relevant to other control procedures (including heuristic forms of control). Rule-based RTC (RB-RTC) strategies, which is the most common form of heuristic control in practice, typically function with pre-defined set points and thresholds embedded in suitable *if-then* operational rules (Garcìa et al., 2015). These RB-RTC methods can be augmented with rainfall predictions, showing an increase in the efficacy of RB-RTC potential (Table 7.1). Before expanding this form of control with nowcast, the nowcast accuracy and potential associated risks should be considered. The application of nowcast-informed RB-RTC for CSO reduction in combined sewer systems, however, has not been studied to the same extent.

Importantly, nowcast accuracy (the ability to correctly predict the rainfall over a given horizon) is not homogeneous and depends on rainfall characteristics (Fabry & Seed, 2009; Imhoff et al., 2020; Lin et al., 2005). The effects of these heterogeneities in nowcast accuracy on UDS modelling and consequently the RTC efficacy has not been explicitly

This chapter is an adapted version of: van der Werf, J.A., Kapelan, Z. and Langeveld, J. (2023). Predictive Heuristic Control: Inferring Risks from Heterogeneous Nowcast Accuracy. *Water, Science and Technology*, doi: 10.2166/wst.2023.027

Table 7.1: Overview of the performance of predictive rule-based real-time control reported in literature

Reference	**RTC Objective**	**Forecast Horizon**	**Performance increase with forecast in RTC**
Gaborit et al. (2013)	TSS Removal	72 hours	66% c.f. no forecast
Gaborit et al. (2016)	TSS Removal	24 hours	42% c.f. no forecast
Bilodeau et al. (2018)	Maximum peak flow from drain*	3 hours	43% c.f. no control
Ibrahim (2020)	Maximum peak flow from basin	Not Specified	56.2% c.f. no control

**It should be noted that this is one of the criteria assessed, found to be most comparable to CSO reduction*

considered in existing forecast induced uncertainty studies (Achleitner et al., 2009; Löwe et al., 2016; Schellart et al., 2014) where rainfall nowcast uncertainty is commonly generated through the addition of homogeneous Gaussian noise on existing rainfall data (Pleau et al., 2001; Svensen et al., 2021). Given the complex nature of nowcast uncertainty, this can lead to inaccurate conclusions being drawn on the influence of nowcast uncertainty on the performance of RTC strategies and should therefore be avoided.

7

This chapter therefore aims to develop efficient, nowcast-informed RB-RTC strategies and to assess if there are risks associated with heterogeneous nowcast accuracy. Furthermore, it aims to assess if these risks can be directly inferred from nowcast and rainfall data. These strategies were developed based on the case study of the UDS connected to WWTP Dokhaven (see Chapter 3.3 for further details on the UDS layout)

7.1. Methodology

To establish the potential influence of rainfall nowcast accuracy on the performance of nowcast-informed heuristic control procedures, a methodology comprising of several steps has been developed (Figure 7.1). Firstly, rainfall data (nowcast and observed) is obtained and discretised into separate rainfall events, followed by the creation of a RB-RTC procedure without the use of nowcast (as a baseline). Then, the potential for operational performance improvement of the UDS through improved control measures is established (Section 7.1.1). Sets of new rules are consequently developed, each utilising specific aspects of the rainfall forecast (e.g. predicted end of the rainfall event or storage capacity exceedance), to capture the potential heterogeneous nature of forecast accuracy . These sets of rules form the new nowcast-informed RB-RTC procedure. The performance using both perfect and real rainfall forecast is then assessed and, if relevant, the risk of performance loss related to these rules is quantified (Section 7.1.2)). This is done by only looking at the forecast accuracy or using a model-based approach to quantify the risk (Section 7.1.2). A qualitative comparison of the findings obtained from both methods is then made and relevant conclusions are drawn.

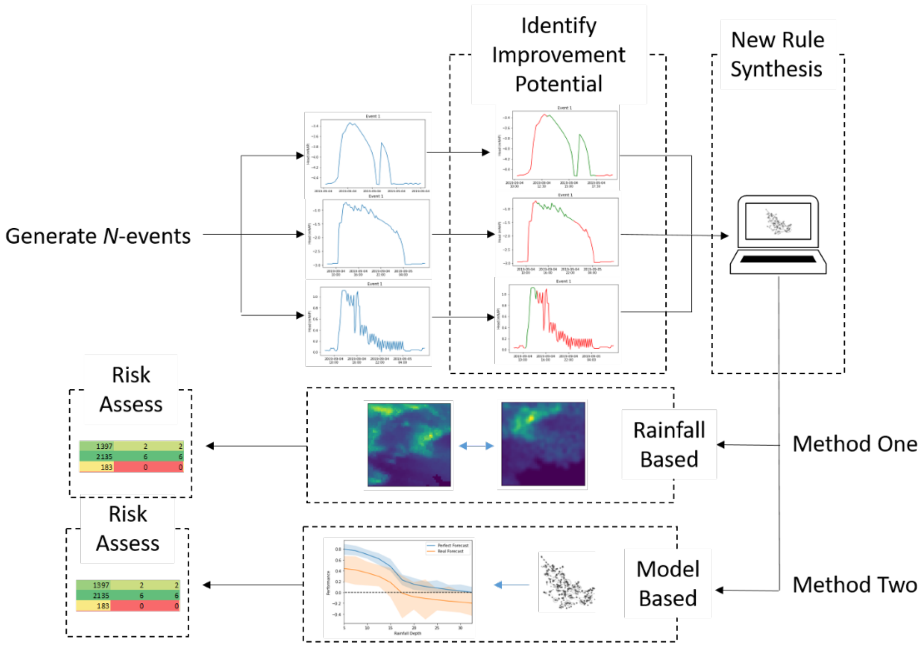


Figure 7.1: Overview of the steps in the methodology. First, events are defined and the models and rainfall are generated. Performance improvement is then assessed, followed by the synthesis of a new, nowcast-informed RB-RTC procedure. The functioning of these procedures is assessed following a model-based and a rainfall-based method. The associated risks are compared in a qualitative manner.

7.1.1. PERFORMANCE IMPROVEMENT ASSESSMENT AND NEW RULE SYNTHESIS

Firstly, available nowcast and observed rainfall datasets have to be obtained. Here, the observed rainfall dataset is a rain-gauge adjusted radar product, following a data assimilation procedure detailed by Overeem et al. (2009). The nowcast data is an open-source product obtained using an advection model based on real-time observation of two C-bands operated by the Royal Netherlands Meteorological Institute (KNMI, see dataplatform.knmi.nl for the online access to the dataset). The rainfall datasets obtained this way then have to be discretised into individual rainfall events, to allow for an event-based risk assessment (using the methodology set out in Section 7.1.2). Here, the definition of a rainfall event uses a minimum inter-event time (MIT) of 12 hours based on the rain-gauge adjusted radar product, recommended as this is the approximate emptying time of the system (Joo et al., 2013). The nowcast available was converted using Equation 6.5 (see Chapter 6).

Before a RB-RTC procedure through the inclusion of nowcast is considered, an analysis of the potential of RTC-based operational improvement has to be done, relative to existing UDS operation without nowcast. Using the previously established rainfall events, the model-based performance evaluation methodology presented by van Daal et al. (2017) is followed to determine the current functioning of the RTC. For the same events the adjusted absolute central basin approach (aCBA), previously used in the computation of performance indicators (Chapter 4), is used to compute the maximum performance potential of the UDS through RTC, while the former gives an indication on the current performance of the UDS. The adjusted aCBA computes the maximum achievable performance of the current UDS configuration by iteratively lumping pumped UDS sections into a single basin with the aim to compute the minimum CSO volume theoretically possible (see Chapter 4 for a more detailed breakdown of this previously developed method).

Rainfall events are then ranked based on the difference between the predicted performance and maximum achievable performance. Events with the largest difference are analysed by first identifying the location and timing of the CSO events. Then, the settings of the actuators influencing the CSO location are analysed before, during and after the CSO event. Potential improvements are noted by using expert judgement of the dynamics of the system, by assessing the filling degrees in the UDS up- and downstream of an activated in combination with actuator settings to see if local improvements could have been realised.

Based on this performance improvement potential, updated rules expanding on the existing heuristic RTC procedure are developed. Here, the existing RB-RTC is updated into a nowcast-informed RB-RTC through two types of rule augmentations: (1) nowcast-based bifurcations at the existing rules (where *if-then* logic is added to the current *if-then* rule) and (2) replacement of the existing rules by outputs of a nowcast-forced model. To assess the effect of potential nowcast accuracy heterogeneity, the nowcast-informed RB-RTC should include augmentations at different phases (beginning, during and at the end of the rainfall event) and based on different rainfall properties (total depth or intensity).

The implementation of the control rules can either be: (1) nowcast-based heuristic control or (2) model-informed heuristic control. Nowcast-based heuristic control directly uses the nowcast data within the RB-RTC procedure (e.g. if predicted rainfall depth < 0.5 mm, then pump off). Conversely, the model-informed heuristic control uses the nowcast as rainfall forcing in the (simplified) model of the UDS, making the RB-RTC procedure dependent on the filling degree predicted through the UDS model. In the model-informed heuristic control procedure, the monitoring data available is used to generate the initial conditions of the model, and the available nowcast data is thereafter used as the forcing of the model. Every set of updated nowcast-informed rules are implemented and simulated separately (see Section 7.1.2 for the assessment methodologies used).

The rules for perfect nowcast data (using the observed rainfall) are developed following a heuristic approach, relying on UDS understanding rather than formal optimisation to develop and calibrate the rules. This form of rule generation was deemed sufficient as long as the operational performance with respect to the control objective of the nowcast-informed RB-RTC using perfect prediction was higher compared to the baseline RB-RTC.

7.1.2. NOWCAST RB-RTC RISK ASSESSMENT

Two types of risks associated with various forms of uncertainties in a real-time optimisation context were previously identified (see previous chapter): (1) risk of UDS performance loss and (2) risk of operational deterioration of UDS. The former indicates a decreased improvement compared to the perfect prediction scenario, but a net increase in UDS operational performance compared to a baseline , and the latter means a loss of performance compared to the baseline, induced by operational uncertainties.

To assess these potential risks, two methods are compared: (1) assessing the accuracy of the nowcast dependent on features (related to, for example, depth or stage of the rainfall) used in the RB-RTC procedure and (2) comparing the model-informed performance using real nowcast data as the input of the RB-RTC procedure. The first method does not require neither UDS nor RTC modelling and is therefore the preferred method. The validity of this method, however, can only be established if the risks are first calculated through a model-based risk assessment, the methodology which is further expanded on in Section 7.1.2. Therefore, the two methods are compared here to assess if the same conclusions can be drawn in which case the forecast-based risk assessment would be preferred, otherwise the model-based risk assessment has to be used.

FORECAST-BASED RISK ASSESSMENT

To assess if there is heterogeneity in the nowcast accuracy, several key properties are considered, keeping the nature of the use of the nowcast within the RB-RTC procedure in mind. The key properties assessed for heterogeneity in accuracy are: (1) accuracies dependent on the stage of the rainfall event (start, middle or end), (2) accuracy dependent on forecast horizon, (3) forecast consistency and its relation to accuracy and (4) accuracy dependent on total rainfall depth. These key properties are further explained below.

As the prediction horizon used in this work (2 hours) is significantly smaller than the MIT (12 hours), sub-event are discretised from the larger events, with the sub-MIT set to 3 hours (thereby keeping no-rain time periods within the assessed data).

Depth and Binary Prediction

Various metrics have been used in the performance evaluation of radar rainfall nowcasting techniques (Ashok & Pekkat, 2022). In the nowcast-informed RB-RTC procedure the forecast induced bifurcations are frequently dependent on a pre-set, stationary threshold. For this reason, the rain-gauge adjusted and nowcast datasets are transformed into binary datasets using multiple thresholds, to get a set of binary datasets in combination with the numerical predictions. For every updated prediction in the dataset, the sum of the forecasted rainfall over the horizon is compared to the threshold, with exceedance of the threshold amounting to a True and non-exceedance to a False. This will give an insight if the predictability of events depends on the rainfall depth. The same procedure is applied to the rain-gauge adjusted dataset, using the same forecasting horizon. To assess the strength of the binary predictions, both the probability of detection (POD) and specificity (SPC) are estimated as follows:

$$POD = \frac{TP}{TP + FN} \tag{7.1}$$

$$SPC = \frac{TN}{TN + FP} \tag{7.2}$$

where TP is the number of true positives (correctly predicted *True* values), FN is the number of false negatives (wrongly predicted *True* values), TN is the number of true negatives (correctly predicted *False* values) and FP is the number of false positive (wrongly predicted *False* values).

Temporal Heterogeneity

Temporal heterogeneity in the forecast accuracy refers to the ability of the nowcast algorithm's ability to predict the dynamics at the start, during or end of a rainfall event. To assess this heterogeneity, two discretisation techniques are used: time-dependent and depth-dependent discretisation. In the former, each rainfall event is discretised in 10 equal parts with the same duration of the event and the latter follow a 10 equal part discretisation using the total rainfall depth to discretise the event (see Figure 7.2). The POD and SPC are computed at every stage and used to generate a distribution of POD and SPC values. Kolmogorov-Smirnov test (Young, 1977) is used to assess if these distributions differ (for each discretised part of the rainfall event). Adjacent distribution of POD and SPC values are compared and assessed for statistically significant ($p < 0.05$) differences.

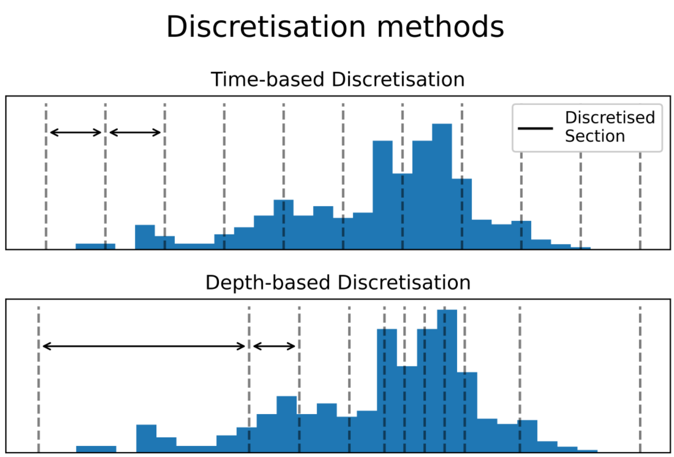


Figure 7.2: Difference between the time-based and depth-based discretisation methods. For the depth-based method, the cumulative depth is used to generate 10 sections with equal total rainfall depths.

Forecast Horizon Influence

The negative influence of the increasing forecasting horizon on the nowcast accuracy has previously been shown (Achleitner et al., 2009). To deal with this in a real-time optimisation setting, a discount factor, used to change the relative importance of current performance to future performance, is commonly employed (Tian et al., 2022; Vezzaro & Grum, 2014). From a heuristic control perspective, the understanding of the accuracy over the prediction horizon can influence the horizon used within the RB-RTC. Here, at every updated prediction, the cumulative prediction over the available 5-minute increments is compared to the rain-gauge adjusted radar data, using the following root-mean-square error:

$$RMSE_T = \sqrt{\frac{\sum_{i=1}^{N}\sum_{t=0}^{T} x_{i,t} - \sum_{t=0}^{T} \hat{x}_{i,t}}{N}} \tag{7.3}$$

where the $RMSE_t$ is the root-mean-square deviation for horizon of length T, $x_{i,j}$ is the i^{th} rain-gauge adjusted rainfall at time-step t within the prediction horizon, $\hat{x}_{i,t}$ is the i^{th} predicted rainfall at time-step t within the prediction horizon and N is the total number of samples in the dataset. The change in the $RMSE_T$ of the cumulative predicted rainfall is assessed here, to better understand if the summation over the horizon allows for a self-correcting mechanism, or if an increased deviation is observed (as per the individual predictive strength evaluated by Imhoff et al. (2020)).

Nowcast Consistency

7

The level of nowcast consistency refers to the level of change in the given sub-section of the nowcast as the model is continuously updated. To assess this, a sub-section of the data (in this case half of the forecast horizon) is tracked as it approaches the moment of implementation (see Figure 7.3 on the left). At the point of implementation in the RB-RTC performance point, the tracked windows are assessed using a correlation coefficient matrix, and the final level of nowcast consistency is defined as the mean value of the lower triangular matrix, excluding the correlation matrix diagonal (see Figure 7.3 on the right). A negative relation between the mean correlation and the nowcast $RMSE$ over the $0-n$ horizon is assumed here.

The risks associated with the inclusion of different nowcast attributes cannot be directly inferred from the statistical methods described previously, given the non-linear nature of RTC performance to rainfall characteristics (Vezzaro, 2022). For this reason, a model-based risk assessment method is needed to quantify the risk associated with the nowcast accuracy properties assessed.

MODEL-BASED RISK ASSESSMENT

Two previously defined risks, the risks of performance loss and operational deterioration, related to the various analysed aspects of the nowcast rainfall data need to be computed. To achieve this, the updated procedures shown in Section 7.1.1 are implemented

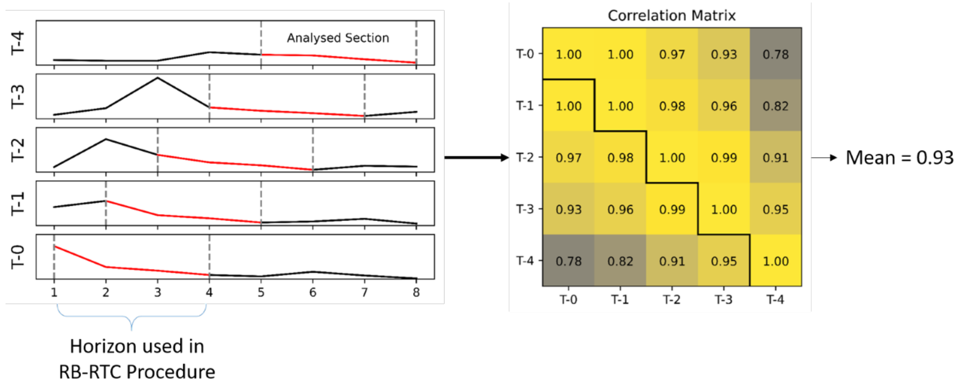


Figure 7.3: Method used for the assessment of prediction consistency. A sub-section of the nowcast data is selected and tracked, and a mean value of a part of the correlation matrix (below the black line in the figure on the right) is calculated as a way to quantify the consistency. The x-axis indicate the number of time steps included, here a time step represents 15 minutes, resulting in a horizon of two hours in total.

in the EPA-SWMM 5.1 software (Rossman, 2015) through the PySWMM python interface (McDonnell et al., 2020). To gain better understanding of the performance and its dynamics, reading of the SWMM output-files is done through the python SWMM API (Pichler, 2022). Both full-hydrodynamic (FH) and simplified models can be used for the model-based risk assessment providing adequate model calibration has been conducted. Here, a simplified model of the case study UDS was used, given the too inhibitive computational inefficiency associated with FH-models.

With the new rules implemented, N-rainfall events representative of the spread of rainfall characteristics typical for the used case study are simulated using the aforementioned SWMM model. The number of rainfall events used depends on the available data and computational efficiency of the used SWMM model, noting that it is recommended to use multiple years of data where possible (van Daal et al., 2017). Each simulation is done using the observed rainfall as the nowcast data (perfect forecast) and another using real nowcast data available in real time through the KNMI for RTC purposes. The perfect and real forecasts outputs are then compared to the established baseline (the RB-RTC procedure set up prior to the inclusion of nowcast data). The aforementioned risks of performance loss and operative deterioration associated with each set of nowcast-informed RB-RTC procedures are then calculated by comparing the performances in two simulations with the baseline RB-RTC performance.

7.1.3. Risk Assessment Comparison

The *a-priori* implications determined through the nowcast-based risk assessment (Section 7.1.1) are compared to the model-based risk assessment method. As the risk of operational deterioration and performance loss are directly quantified through the model-based risk assessment and the nowcast-based risk assessment has to infer these based on various nowcast metrics, the comparison between the two methods cannot be directly quantitative. The operational risks (both operational deterioration and performance loss) related to each set of nowcast-informed rules, determined through the model-based risk assessment, are therefore ranked first (from highest to lowest risk). This ranking is then compared to the relative performance of the nowcast property associated with the nowcast-informed rules, to see if a high risk is associated with a relative poor performance in nowcast accuracy.

7.1.4. CONTROL PROCEDURE AND CASE STUDY

The above described methodology was applied to the WWTP Dokhaven Catchment (see Chapter 3). Here, a short recap of the current control procedure as per the CAS 2.0 project, is presented, but for catchment details the reader is referred to Chapter 3.3.5. The CAS 2.0 project details set points for 52 pumping stations (including the pumped CSOs) in the catchment. The development and implementation of the baseline RB-RTC (upon which the nowcast rules were developed here) was done as part of the aforementioned CAS2.0 project, as described in Langeveld et al. (2022b). The key logic in the CAS 2.0 RB-RTC procedure is a change in set points of pumping stations (by either partially switching the pumps off to protect downstream districts or switching the pumps at CSOs on), dependent on the upstream and downstream filling degrees (using a 80% filling degree (FD) as the set threshold). A graphical representation displaying this main logic is shown in Figure 3.10.

The control strategy was set up as a multi-objective problem, aiming to reduce the frequency and volume of CSO discharges to the urban canals first, then the total CSO volume and lastly reduction of overloading the WWTP. As no formal real-time optimisation algorithm was used, a hierarchical form of control objective, namely the reduction of CSO volumes discharged to the urban canals, was used as opposed to a weighted CSO volume synthesis (as proposed by Vezzaro and Grum (2014). When reporting the results, total CSO volume is used as means to indicate the improvement of the system performance, unless an increase in the CSO volume towards the urban canals has been caused. Due to physical constraints of the pumping stations configurations, the minimum sampling interval of the pumps (the time between adjusting the pumping station set points) is 15 minutes. This sampling interval is therefore used within the model-based risk assessment.

The existing RTC rules are augmented using six different sets of new rules (i.e. new RTC procedures), utilising nowcast data in different ways (Table 7.2). Given the presence of the CSO pumps, some of the nowcast-informed rules apply only to these actuators (RTC procedure 1). The other RTC procedures make the operation of all pumping stations in the original RB-RTC, using different total depths for activation (RTC Procedures 3 and 5), event phases (RTC Procedures 1 and 2), spatially aggregated data (RTC Procedure 6) or fully relying on the nowcast and current data within the established RB-RTC (Procedure 4). More details including examples of the developed procedures can be found in Appendix D (Section D.1 and Figures D.1-D.6). A detailed breakdown of the potential for RTC based improvement of the UDS is shown in Appendix D Section D.2.

To assess the updated RB-RTC performance, 95 rainfall events (generated following

Table 7.2: Description of the updated rules, including the relevant nowcast properties used in the rule, used to assess the impact of nowcast uncertainty on the efficacy of the improved RB-RTC procedure

Procedure ID	**RB-RTC type**	**Nowcast properties**	**Description**
1	Nowcast-based Heuristic Control	End of the event predicted	If the end of an events is detected, the CSO pumps are switched off
2	Nowcast-Based Heuristic Control	End of the event predicted	If the end of an event is detected, the entire system switches back to < 80% FD conditions
3	Model-Informed Heuristic Control	Total Predicted Volume throughout the event	Following the RB-RTC rules when > 90% FD is predicted
4	Model-Informed Heuristics Control	Total Predicted Volume throughout the event	Following the RB-RTC rules when > 80% FD is predicted
5	Model-Informed Heuristic Control	Tracked hour in advance	Following the RB-RTC rules when > 90% FD threshold was exceeded for at least half of the predictions in the tracked hour
6	Model-Informed Heuristic Control	Tracked hour over connected upstream and downstream catchments	Following the RB-RTC rules when > 80% FD threshold was exceeded for the district or the upstream or the downstream districts for at least half of the predictions in the tracked hour

the definition with an MIT of 12 hours) with reliable data for both the nowcast and the rain-gauge adjusted datasets were identified. These contain rainfall events with return periods of up to 2 years (Figure 7.4).

7.2. RESULTS

The following section sets out the potential for operational performance improvement first, followed by the results from the risk analysis based on the available nowcast data and the model-based risk assessment results. The two methods are then compared, followed by a discussion of the results and their implications for practical nowcast based RB-RTC implementation.

7.2.1. OPERATIONAL PERFORMANCE POTENTIAL

The potential for performance improvement compared to the baseline RB-RTC was assessed for the 95 events previously described. Based on the results obtained using the aCBA method a total CSO volume reduction of 37.2% was possible through optimal operation of the UDS when compared to the baseline. For rainfall events with a smaller total rainfall depth, complete preventions of CSOs have been achieved. For larger rainfall events, the maximum CSO volume reduction was 5.8%. This is consistent with previous results showing the highest potential of RTC impact in the events with low to mid rainfall depths (see Chapter 2).

7.2.2. FORECAST ACCURACY AND RISKS

Rainfall Depth

The predictive ability to correctly predict larger rainfall events is significantly lower compared to smaller rainfall depths (Figure 7.5). The *POD* value drops from 0.93 for predictive ability above 0.25 mm to around 0.5 when the threshold is set to 1mm of cumulative predicted rainfall. This drops further to a POD value of 0.1 for any threshold above 5mm. The *SPC*, on the other hand, increases during the same interval, ending in a maximum value of 0.98 for the larger rainfall events. The abundance of data points is significantly higher for the lower fractions, partially due to the discretisation method of

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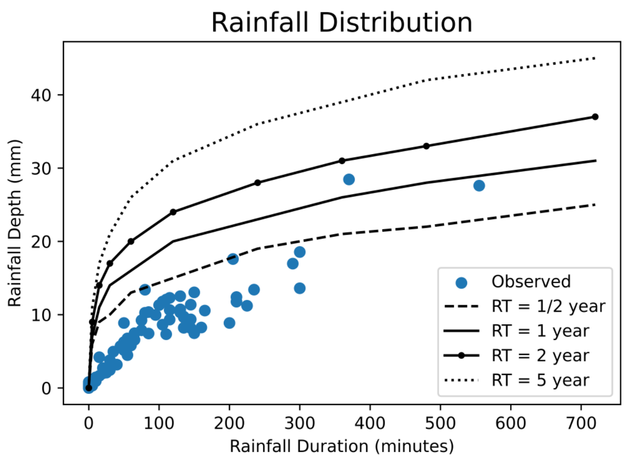

Figure 7.4: Distribution of the rainfall events in the dataset compared to the relevant rainfall statistics (based on Beersma et al. (2019)).

the rainfall events (using an MIT of 12 hours).

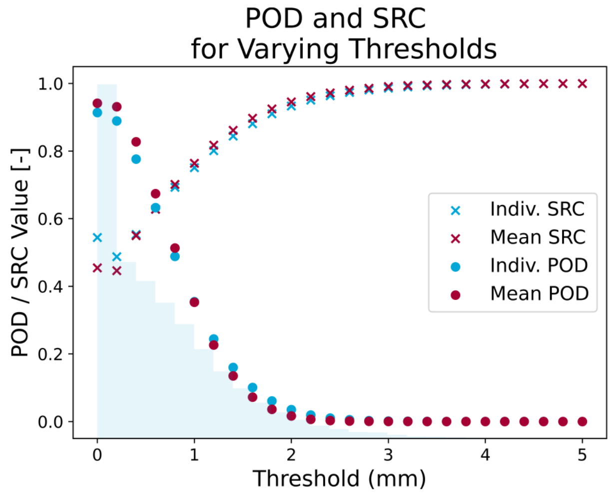

Figure 7.5: Detail of the *POD* and *SPC* values for different threshold rainfall depth over the 2 horizon. The histogram displays the relative abundance in the data set per threshold interval. No significant difference is found when a spatial mean of the predicted rainfall is used rather than individual pixels.

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These results suggest a negative bias within the nowcast data set, as an underestimation of the real rainfall would see a rise in *SPC* and drop in *POD* with an increasing threshold used. This is in line with previous research showing a decreased ability to predict large (often convective) rainfall events (e.g. Foresti et al. (2016) and Pulkkinen et al. (2020)). This has also been shown to lead to decreased discharge forecasts abilities (Imhoff et al., 2022) for hydrological models, conclusions which can largely be extrapolated to UDS.

Forecasting Horizon

The range of the error (difference between the predicted and observed rainfall) increases close to linearly with the increase in length of the forecast horizon (Figure 7.6). The frequency of overestimation is slightly higher, with a mean difference of -0.03 mm and the absolute value of the 25% confidence interval (CI) being larger than the 75% CI (-1.1 and 0.62 mm respectively). Considering the 5-95% CI, however, the errors indicate an opposite trend, whereby the nowcast underestimates the larger, observed values (-2.3 and 4.1 mm respectively). This implies potentially reduced control potential through nowcast inclusion when directly using the cumulative values, particularly when relatively large volumes are predicted (mainly at the start and during a rainfall event). Considering the mean difference over the catchment (using the mean of the cumulative rainfall over all the pixels, see Figure 7.6a), a similar trend can be observed, although the relatively large underestimations do seem to have smoothened out when considering spatial means. Despite the wide range in pixel value difference in the 5-95% CI range, the 25-75% CI bands could be small enough to have meaningful potential in a UDS control strategy and the mean difference is close to zero (indicating the absence of a clear bias).

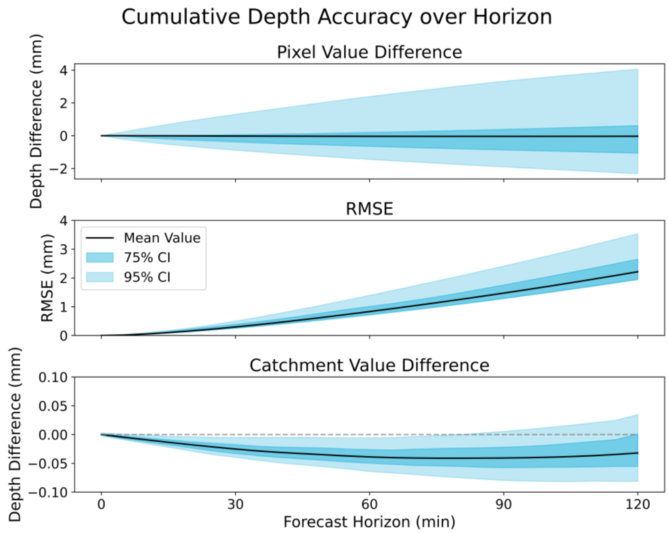

Figure 7.6: Evolution of the uncertainty of the cumulative rainfall depth over the full prediction horizon available (120min) considering the the (a) individual pixel values, (b) RMSE of the individual pixels and (c) the accumulated catchment value difference

The RMSE in the cumulative rainfall prediction (see Figure 7.6b), however, increases exponentially when considering the individual pixel predictions (i.e. the input to any UDS model used in a model-predictive sense). This is in line with previous exponential decrease in the Pearson's correlation as reported by (Imhoff et al., 2020).

Nowcast Consistency

A decreasing trend in the distribution of the total RMSE was observed when comparing the total rainfall forecast for an hour horizon to the mean correlation coefficient (used as a metric for the nowcast consistency), as shown in Figure 7.7. This was expected, as a consistent nowcast was assumed to be more reliable. However, when using a normalised RMSE (normalisation by division with the total observed rainfall), no such relation could be seen. The normalised data for the highest consistency (0.95-1.0) has a significantly improved distribution, particularly due to the number of no-rain forecasts within this subset (which have a relatively high predictability). Furthermore, the dataset shows a higher density in the 0.1-0.4 mean correlation coefficient interval. The highest quarter (0.75-1.0) of the mean correlation coefficient only account for 2.35% of the total dataset. Statistically significant recommendations based on the relation between accuracy and consistency can, therefore, not be made. From a control perspective, the additional benefit of only using the nowcast if a certain mean correlation coefficient is reached, cannot be asserted from this data. However, given the lack of a relation between the mean correlation coefficient and the normalised RMSE, it can be assumed that there is little merit in the use of a control procedure based on the tracking of nowcast consistency. The reduction of the nowcast horizon from 120 to 60 minutes within the RB-RTC will likely have a larger impact on the performance due to the relative increased predictive capacity (see Figure 7.6) rather than through the tracking mechanism.

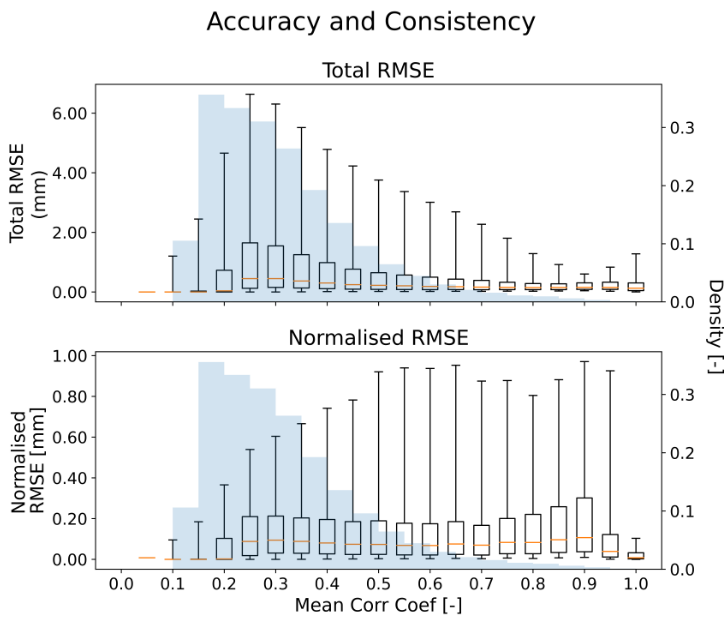

Figure 7.7: Analysis of the consistency of the nowcast compared to the nowcast. The boxplot indicate the RMSE value and normalised RMSE value, for the upper and lower plot respectively, per interval of 0.05 of the mean correlation coefficient. The blue histogram plots the relative occurrence of that interval within the dataset. Whiskers indicate the 5-95% CI.

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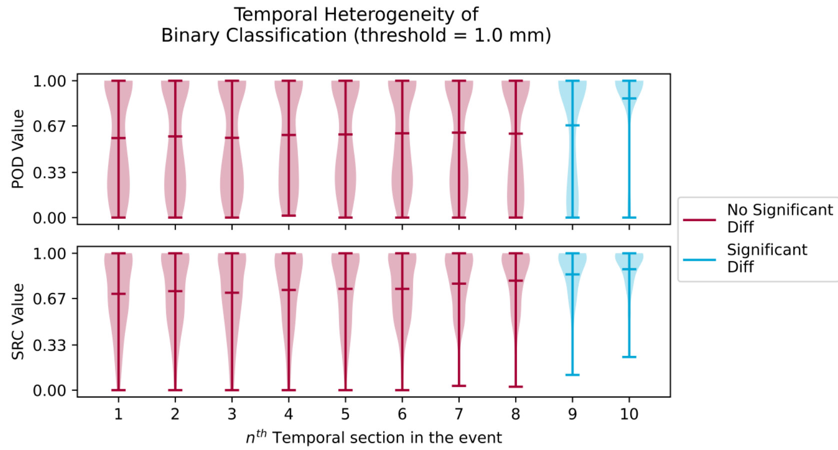
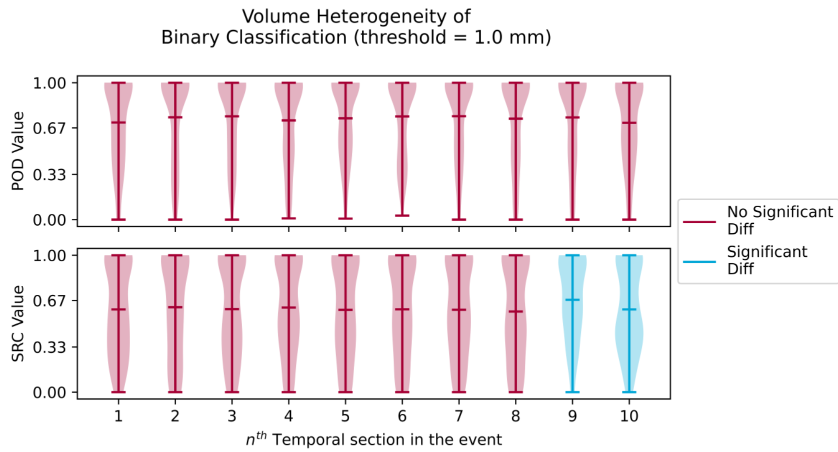
A stronger link between the mean correlation coefficient and the depth of the rainfall event was found. The consistency of the nowcast for 0 to 0.5 mm of rainfall in the forecasted hour was significantly higher ($p < 0.05$) compared to other intervals. This relationship explains the difference between the normalised RMSE and the total RMSE shown in Figure 7.6, as the higher end of the mean correlation coefficient is dominated with low rainfall data (thus having a relatively low RMSE but no difference in normalised RMSE).

Temporal Heterogeneity

Strong statistical evidence ($p < 0.01$ following the KS-test) indicates an improved ability of the prediction at the tail end of the rainfall event, in both the *POD* and *SPC* distributions, following a time-based discretisation method (Figure 7.8a). This shift is dominated by a reduction in the relative prevalence of lower values (0-0.5). Particularly the relative improvement in the *SPC* distribution (assessing the ability to correctly predict the False (no rainfall) values) indicates a good ability to assess if an event has ended. Interestingly, the opposite effect was observed for the volume-based sampling method, with a statistically significant reduction in the *SPC* performance ($p < 0.05$) for the tail end of the rainfall events (Figure 7.8b).



(a)



(b)

Figure 7.8: Results of the temporal discretisation of the rainfall event following the either (a) a time-based or (b) volume-based discretisation methods. Blue distributions indicate significant difference from the previous distribution.

From a control perspective, the time-based discretisation method gives a more accurate representation of the end of the event, as the volume-based method forces the inclusion of rainfall data. The implementation of end-of-event logic (i.e. switching off CSO pumps when no more rain is expected) will follow the time-based implementation, meaning that this form of control is unlikely to be strongly affected by nowcast induced errors.

7.2.3. MODEL-BASED RISK ASSESSMENT

Using the simplified UDS simulation model, the performance of the updated RB-RTC procedures was assessed. When the perfect nowcast data is used, all the updated procedures outperform the baseline RB-RTC (Figure 7.9), with limited risk of operational deterioration. In this case RTC procedure 4 showed the highest total CSO volume reduction potential (14.6% or 10.5mm), followed by Procedure 3 (12.9% or 9.3mm), Procedure 2 (10.9% or 7.8mm) Procedure 6 (10.6%, 8.1mm), Procedure 1 (9.8%, 7.1mm) and Procedure 5 (8.7%, 6.9mm). Despite this decrease in total CSO volume, a risk of operational deterioration (i.e. existence of an event with worse performance compared to the baseline) was present for all updated RTC procedures except Procedure 1. However, the minor increases in CSO frequency and total volumes in Procedures 2-6 were offset in all cases by the corresponding gains made through the updated RB-RTC procedures resulting in the negation of small events.

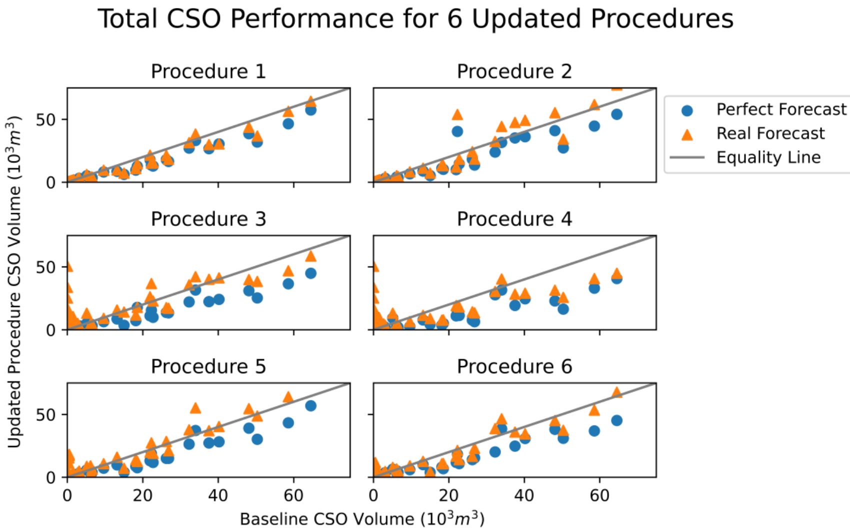


Figure 7.9: Performance overview for the 6 updated RB-RTC procedures, considering both perfect and real nowcast data.

However, when the real nowcast data is used, a considerable risk of both performance loss and operational deterioration is noted for all updated RB-RTC procedures (Figure 7.9). Only two RTC procedures (Procedures 1 and 2) reduced the total CSO volume of the operation under the real nowcast scenarios, but significantly less compared to the theoretical potential (Table 7.3). Procedures 4 and 6 show a minor increase in the CSO reduction compared to the baseline (both 0.8%). However, most notably, Procedures 3 and 5 show a net increase in the total CSO volume of 17.7% and 15.7%, respectively. In the case of Procedure 3, this increase in volume is predominantly caused by the pumped CSOs being activated unnecessarily, shown in Figure 7.9 as the column on the low part of the baseline performance. As a result, 40.8% of the events within the dataset had a worse performance compared to the baseline RB-RTC. Procedure 5 also resulted in a number of events with deteriorated UDS operation (25.0%), but the relative CSO increase was caused less by the unnecessary CSO pumping and more through a decreased performance throughout all the rainfall events.

Table 7.3: The performance of the six procedures compared to the baseline, relative increase to the perfect nowcast data and frequency of deterioration (Total CSO volume higher than the baseline RB-RTC results)

Procedure ID	CSO volume reduction relative to baseline RB-RTC	Increase in CSO volume compared to Perfect Nowcast	Percentage of rainfall events with deteriorated operation relative to Perfect Nowcast
1	7.0% / 5.0mm	3.1%	2.6%
2	1.3% / 0.95mm	10.9%	10.5%
3	-17.7% / -12.6mm	35.3%	40.8%
4	-0.8% / -0.59mm	18.1%	13.9%
5	-15.7% / -11.2mm	28.1%	25.0%
6	-0.8% / -0.59mm	13.7%	13.1%

RTC of UDS aims to utilise the existing UDS optimally, by ensuring the optimal distribution of runoff throughout the system. Consequentially, if there is a failure throughout the system (i.e. nowcast inaccuracies) the possibility of adverse effects increases. The two control systems which had the highest performance decrease (Procedures 3 and 5) were both designed to: (1) use the numerical output of the nowcast algorithms directly and (2) operate closer to the total filling of the UDS. No relation between the apparent risk and the RTC potential (i.e. the performance using the perfect data) was found.

Finally, in the shown case study it was observed that the augmentation of the RB-RTC with nowcast data leads to significant decrease in operational performance compared to both perfect forecast case and the baseline RB-RTC. This is despite the potential of nowcast to decrease the total CSO volume for all analysed procedures.

7.2.4. COMPARATIVE ASSESSMENT

Of the six RTC procedures presented here, Procedure 1 (relying on the correct prediction at the end of the event to switch off the pumped CSOs) was able to reduce the CSO volume in both the perfect and real nowcast cases. This is consistent with the ability of the nowcast model to predict the end of a rainfall event (as previously shown in Figure 7.8).

Although this accuracy is not perfect (mean *SPC* of 0.81), the effect of incorrect predictions appear to have a small impact on the UDS operational performance (3% CSO volume increase compared to the perfect baseline).

Conversely, a higher risk of operational deterioration was observed when the RB-RTC procedure sets the CSO pump settings directly dependent on the forcing of the forecasted rainfall depth in a modelled setting. This was further exacerbated by switching on the pumped CSOs if a higher threshold was predicted (using a filling degree of 0.9 as opposed to 0.8). As these procedures used the entire forecast horizon to predict the depth (with an activation only occurring at the higher end of the rainfall prediction), both rely on two of the weakest points identified in the nowcast data. These are using the direct numerical prediction over the full horizon (120 minutes) and using a high threshold for activation of the rules. Procedure 5 relied on a consistent forecast in order to activate, though, as also shown through the nowcast performance assessment, this did not increase the robustness of the control procedure.

The results from the nowcast accuracy assessment yielded similar trends compared to the model-based risk assessment methodology. Although it is not possible to quantify the risks directly from the nowcast data, due to aforementioned non-linearities and the nature of the risks identified here, the statistical analysis of nowcast data gives a strong indication on how the nowcast can be included in future RB-RTC strategies. This, in turn, allows bypassing the extensive model-based analyses, as presented here, and allows operators to make informed decisions based on less data and model outputs.

7.3. Discussion

When comparing the performance loss related to the nowcast accuracy with real-time RTC optimisation procedures, the self-adjusting mechanism reported to reduce the impact (Courdent et al., 2015; Fiorelli et al., 2013) was not observed in the model-based risk assessment results. This is likely to be a result of the relatively long sampling interval and the design of the updated RB-RTC procedures. However, it is possible that an increased level of risk could be an inherent drawback of RB-RTC including nowcast compared to real-time optimisation procedures. Additional evidence, based on different case studies following the presented methodology here, is necessary to ascertain the latter and attribute and quantify the relative importance of the former two.

Furthermore, studies which investigate the impact of nowcast uncertainty through synthetic errors (e.g. Svensen et al. (2021)) are likely to misreport on the potential impacts of nowcast uncertainties, given the dynamics observed here. Use of real nowcast algorithms in combination with real observed data is therefore considered to be a must for applicable results.

Although the methodology presented here is applicable to other case studies, the main findings depend on the available nowcast data (both events within the dataset and the forecast model used to generate the nowcast data) and hence the results obtain in this work may therefore not be directly transferable (He et al., 2013; Imhoff et al., 2020). The nowcast data accuracy assessment, as presented here, should therefore be done prior to the implementation of nowcast-included RB-RTC in other case studies, to ensure similar dynamics are observed.

With the rise of machine learning (ML) application in the field of rainfall nowcasting (Amini et al., 2022; Ravuri et al., 2021), new nowcasting methods which focus on specific rainfall properties (i.e. timing or magnitude of the start of an event, total sum of the horizon or prediction of the ending of the event) could improve the functionality of RB-RTC augmented with nowcast. Similarly, the use of ensemble forecasts has previously been shown to be beneficial in an RTC context (Balla et al., 2020; Courdent et al., 2015; He et al., 2013). Understanding the differences within the ensemble forecast can further decrease potential uncertainties and their effect on the operation of UDS.

Nowcast-informed RTC was also applied to the Eindhoven case in a study performed by Santágueda (2021). However, the procedures developed (which was impact-based, modelled in the DHI WEST environment) did not result in sufficient behavioural changes in the actuators to allow for an in-depth analysis of the influence of the uncertainties on the control procedure. The results of the control measure only managed to reduce the CSO total by around 3% in the developed control procedure.

7.4. Conclusions and Future Outlook

This Chapter aimed to understand how heterogeneity in nowcast accuracy, dependent on varying rainfall properties, can affect and be used in a rule-based real-time control (RB-RTC) procedure for the improvement of urban drainage system (UDS) operation. Using both perfect and real nowcast rainfall data in the Rotterdam UDS, a model-based study was performed to assess the risk of six different RB-RTC procedures potentially resulting in performance loss or operational deterioration of the analysed UDS. Based on the results obtained he following conclusions could be drawn:

- Multiple forms of nowcast-informed RB-RTC can significantly decrease the pollution load from UDS when using perfect nowcast data. However, significant risks are associated with using real nowcast data to control the UDS resulting, in some cases, in significantly increasing the CSO frequency and volume;

- Nowcast accuracy is heterogeneous and depends on the stage and depth of the rainfall event. The nowcast data indicated a strong predictability of the end of a rainfall event but poor performance at the start and in the middle of an event, particularly when larger rainfall depths were observed;

- This heterogeneity relates directly to risks of operative deterioration and performance loss, as the impact of the uncertainty can be inferred directly from the nowcast data. Using these inferred risks, decision can be made about the development of nowcast-informed RB-RTC;

- The dynamics related to heuristic control versus real-time optimisation control in the context of uncertain forecast differ, as the heuristic control does not appear to have a strong self-correcting mechanism. A real-time optimisation strategy might therefore be a more robust implementation of nowcast-informed forms of control.

Based on these conclusions, additional research is needed to understand if the results and conclusions drawn from this case study are transferable to other UDSs. Furthermore, the ability to formally optimise the nowcast-informed RB-RTC using real nowcast data was not assessed here and a comparative assessed of a nowcast-informed RB-RTC calibrated on real and perfect data should be done. Additional measures to ensure the resilience of heuristic control to uncertain rainfall data should be investigated.

The contrast between the conclusions drawn here and those in the previous chapter (pertaining to the influence of various uncertainties on real-time optimisation procedures) are clear. Indeed, the influence of rainfall nowcast uncertainty on the functioning of heuristic based control measures were shown to be highly influential, though can be mitigated against when using the nowcast in an informed manner. This is a strong indication that real-time optimisation measures should be seriously considered when looking at improving the performance of real-time control applied to urban drainage systems, as the influence of uncertainties on their operation are not dissimilar to those in nowcast informed improvements.

8

LONG TERM CHANGES

IN the previous chapters, the effects of various errors induced by uncertain information in a model predictive control (MPC) procedure are assessed and discussed. Over the lifespan of an RTC strategy, the controlled urban drainage system (UDS), is constantly changing (see Chapter 2 for an overview of the potential changes), thereby inducing additional errors as the physical UDS is no longer aligned with the models underpinning the control procedures.

These system changes can increase the potential of RTC procedures. The implementation of RTC combined with blue-green (BG) infrastructure or Sustainable Urban Drainage Systems (SUDS) has gained attention in recent years. This co-implementation was shown to decrease CSO volumes more effectively compared to either strategy on its own (Altobelli et al., 2020). A heuristic-based framework for the co-implementation of RTC and BG infrastructure was later devised and showed similar increased potential (Jean et al., 2021). In an extension of the framework, the implementation of real-time optimisation methods in the form of model predictive control (MPC) in conjunction with BG infrastructure showed further increased potential (Jean et al., 2022).

These RTC strategies were specifically designed with the implementation of new BG infrastructure in mind. This assumes a high level of integration between urban developers and operators, which in practice has proved challenging (Manny, 2023; Nieuwenhuis et al., 2021). Furthermore, deployment of BG infrastructure in the urban environment might consider multiple criteria with the effect on the in-sewer hydrodynamics only forming a small part in the decision-making process (Donati et al., 2022; Seyedashraf et al., 2022; Suárez-Inclán et al., 2022). This recent shift is likely to further complicate the integration between urban developers and operators, potentially exacerbating the loss of UDS performance related to the RTC procedure. Additionally, a difference between the planning of urban development and the final built environment might arise (Strohbach et al., 2019; Vollaers et al., 2021), affecting the UDS dynamics and thereby potentially the optimal RTC procedure.

Alongside the implementation of BG infrastructure, (re-)densification within existing city limits to create compacter urban areas is a commonly observed transition around the world (Broitman & Koomen, 2015; Næss et al., 2020; Shahtahmassebi et al., 2016). Associated with an increase in the level of imperviousness in an urban environment, the increase in population is projected to increase the runoff loading of the UDS. An

This chapter is an adapted version of: van der Werf, J.A., Kapelan, Z. and Langeveld, J. (*Under Review*). The Impact of Blue-Green Infrastructure and Urban Area Densification on the Performance of Real-Time Control of Sewer Networks. *Under Review, Water Resources Research* annual increase of around 0.5% in levels of imperviousness was reported (ranging from -0.1 to 0.9%) due to the densification of cities (Nowak & Greenfield, 2012). This increase in imperviousness will increase the local runoff rates, changing the local dynamics and thereby potentially the functioning of the implemented RTC strategy.

These long-term changes have previously been shown to have a significant effect on the functioning of wastewater treatment plants (WWTPs) and should be systematically considered in the design stage (Dominguez & Gujer, 2006). However, the impact of long-term has not been studied for the operation of UDS and understanding how the gradual change of the urban environment can alter the functioning of RTC procedures is one of the key questions towards ensuring the successful implementation of RTC strategies (see Chapter 2). This paper aims to understand the longevity of real-time control strategies for urban drainage systems with respect to gradual configurational changes happening in the urban environment.

8.1. METHODOLOGY

This section sets out the framework proposed to assess the impact of gradual changes arising from long-term urban area transitions on the efficacy of previously implemented real-time control strategies. Gradual changes are defined here as changes to the surface or subsurface in the urban environment that do not significantly alter the dynamics of that system (e.g. local conduit replacement, tiling of a garden, the addition of small-scale BG infrastructure). The combination of these gradual changes aggregates over years to form the transitional paths in the system which, cumulatively, can have an impact on the in-sewer dynamics. Here, only above-surface gradual changes are considered in the urban transitions modelled, more specifically the densification of the urban environment and the implementation of BG infrastructure. These changes are implemented in a model-based framework after the performance of the current RTC configurations is calculated. A schematisation of the methodology can be found in Figure 8.1.

Section 8.1.1 sets out two methods used to generate the transitional paths to assess their impact on the used RTC procedure. Details on the scenarios and control procedures used can be found there. Both the UDS connected to WWTP Hoogvliet and the Riool-Zuid UDS were used in this chapter, as detailed in the coming section.

8.1.1. URBAN TRANSITIONS

To generate future states of the UDS to be assessed, two methods for generating transitional paths have been used: (1) detailed implementation of the modelled urban transitions (based on a detailed full-hydrodynamic model, denoted here as detailed urban transitions) or using a (2) probabilistic, conceptual implementation of transitions (based on a conceptual model of the UDS, denoted here as stochastic urban transitions). The former allows for a more detailed assessment and the latter allows for stochastic analyses. The urban transitions assessed can be either based on planned changes to the UDS, to assess their relative impact, or exploratory modelling to understand the potential impacts of different transitions on the functioning of RTC procedures. Both methods are

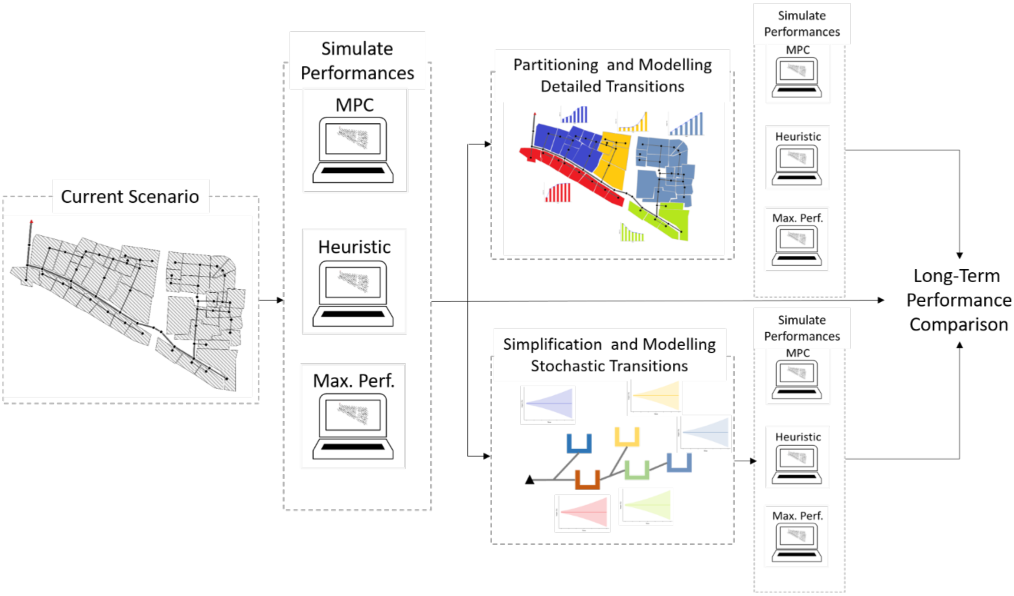


Figure 8.1: Schemetisation of the methodology presented here.

used to either generate scenarios to assess the impact of various urban transitions on the functioning of the RTC strategy, or to evaluate specific transitions which are considered for implementation. The former is used here.

The performance of the RTC procedures used will be evaluated using both the total CSO volumes calculated through the model-based assessment framework described by van Daal et al. (2017) and the absolute RPI from Chapter 4.

DETAILED URBAN TRANSITIONS - EINDHOVEN CASE STUDY

The previously calibrated full-hydrodynamic model (FH) describes the virtual representation of the elements and dynamics of a UDS and allows for a detailed assessment of transitions happening within. As FH models are computationally heavy, random sampling of future states is not feasible. Assessing future scenarios should therefore follow a selective sampling form, such that the result allows for an inference of the relative impact of the analysed transitions. This selective sampling can either be based on concrete future plans or following a deviant case sampling structure (Draucker et al., 2007). Here we follow the latter as it highlights the potential impacts of urban transitions on the performance of RTC procedures.

Deviant case sampling refers to the sampling technique where extreme cases are used to further understand conditions, consequences and interactions within a dataset, making it a useful tool for cases where the number of possible simulations is limited. Here, deviant case sampling is used to make N scenarios of which the impacts of RTC efficacy are assessed. To make these scenarios, the following steps are used: (1) UDS partitioning; (2) transitional definition; (3) scenario creation. These steps are outlined in more detail below.

The first step is to divide the UDS into sections, partitioning the sections based on the location of actuators (schematised in Figure 8.2), adjusted from the partitioning processes used for the design of a decentralised control scheme (Obando et al., 2022), though without the topological distinction. Considering the entire UDS as a graph $G = (V, E)$ where V are the manholes and E the conduits in the UDS. The description of the above-ground sub-catchment linked to the nodes is encoded within V. All actuators are extracted from the set of nodes such that $A \subseteq E$ (highlighted links in red in the UDS shown in Figure 8.2).

A partitioned graph is then formulated using A as the edges of the new graph following $G' = (V', A)$, where $G^{'}$ is the new, partitioned graph and V' is the set of nodes following $V' = \{S_1, S_2, \ldots, S_n\}$ where S_n is the set comprising of the conduits and nodes (including the encoded sub-catchments) for n^{th} part contained by the actuators and the UDS boundaries (the simplified graph on the right in Figure 8.2). If part of the UDS is not clearly contained between actuators, due to multiple paths and loops within the UDS (as is the case of UDS section S4 in Figure 8.2), the non-contained sections are joined within a single set following $G' = (V', A^*)$, with A^* representing a subset of the set of actuators $A^* \subseteq A$ such that V' is fully contained. Here, this simplified model is then implemented in the EPA SWMM5 software (Rossman, 2015).

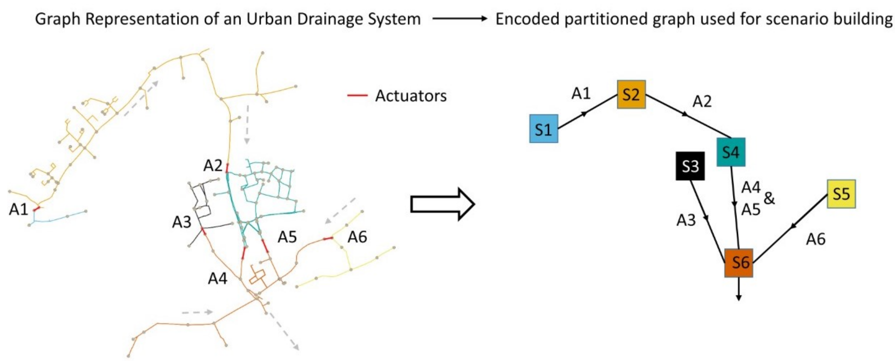


Figure 8.2: Schematic of the graph partitioning applied to an example UDS. Arrows indicate flow directions

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

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

The case study used the assess the transitions implemented in a detailed way in the Riool-Zuid catchment (upstream of PS Aalst) as described in Chapter 3.2. Here, A volume-based control strategy was set up for this catchment, aiming to reduce the total CSO volume discharged through the UDS. The associated objective function is as follows:

$$min \sum_{i=1}^{N} \sum_{t=1}^{T} CSOvol_{i,t} \tag{8.1}$$

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

Three different RTC approaches were used here: RTC based on simple heuristics, RTC based on more advanced heuristic control and an MPC-based RTC. The simple heuristics RTC strategy is based on a single set-point control procedure. Both control stations will limit flow when wet weather flow is detected (the downstream level is above a set threshold). Control Station de Meeren (the downstream most control station) has a target flow rate of 5,000 m^3/h and Control Station Valkenswaard (the upstream most control station) has a target flow rate of 2,500 m^3/h. The advanced heuristic-based RTC procedure computes the flow rate for each control station dependent on the state of the upstream and downstream section (filling, emptying, spilling, stable or dry weather flow), using an optimised lookup table to find a pre-defined set point for each combination of upstream and downstream phase. The procedure is optimised and described (including the definition of the phase) in Chapter 4 and setpoints can be found in Appendix A (Tables A.1-A.2).

A Model Predictive Control (MPC) procedure was also set up. The MPC optimises the setpoints of the two aforementioned control stations using the previously developed simplified model implemented in EPA SWMM5 (see Chapter 4 for the details). Setpoints are optimised at five-minute intervals using the objective function shown in equation (8.1), whilst considering the constraints mentioned above. The MPC architecture used by Sadler et al. (2019) is applied here. A prediction horizon of 2 hours was selected, as this was the horizon for the rainfall nowcast data available. An elitist Genetic Algorithm (Goldberg, 2013) was used to solve the aforementioned optimisation problem over a control horizon of 1 hour, as it has been commonly done in RTC studies over the years (see e.g. Lund et al. (2018) and Rauch and Harremoës (1999) for an overview), also in more recent MPC studies (Abou Rjeily et al., 2018; Eulogi et al., 2020; Li, 2020; Mounce et al., 2019; Rathnayake & Anwar, 2019). The GA has been shown repeatedly to identify the near global optimal solutions in a relatively few iterations (Vasiliev et al., 2022). The set of GA parameters used can be found in Appendix C (Table C.1). The optimisation runs were performed on a desktop PC with a four-core Intel i5-6500 CPU @ 3.20 GHz. Following EPA SWMM5 internal code, the simulation time step is variable, with a minimum step of 5 seconds used for stability reasons.

Four scenarios were set up for the detailed transitions assessment for the Riool-Zuid (upstream of PS Aalst) catchment. The urban transitions were exclusively applied to the sub-catchments in the UDS, thereby changing the effective catchment size (either an increase through densification or a decrease through BG infrastructure implementation). Scenario 1 increases the effective catchment size at the local scale where possible for all the partitioned sections. Scenario 2 decreases the effective catchment sizes in all catchments. Scenarios 3 and 4, on the other hand, combine densification and BG infrastructure implementation, such that the difference between adjacent sections is the highest. Here, this results in an increase and decrease in the effective catchment sizes for the middle part and the other parts respectively (Scenario 3) and vice versa (Scenario 4). Figure 8.3 represents these scenarios visually.

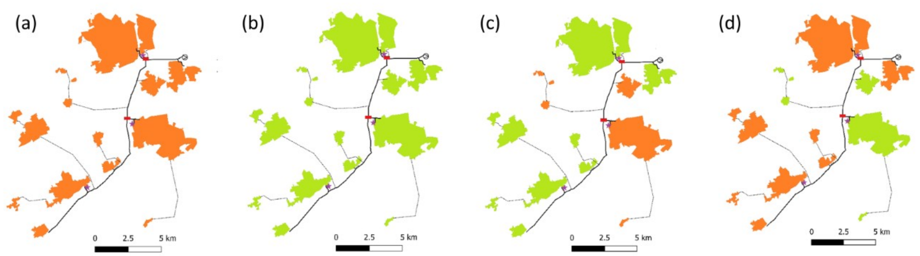


Figure 8.3: Graphical overview of the scenarios, orange denoting areas of densification and green denoting areas with increased BG infrastructure implementation. (a) represents Scenario 1, (b) Scenario 2, (c) Scenario 3 and (d) Scenario 4.

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

15 events using the aforementioned radar rainfall data were used, with total rainfall depth ranging from 5.8-38.7 mm (mean 17.56 mm) with max intensities ranging from 2.2-30.6 mm/hr.

STOCHASTIC URBAN TRANSITIONS - WWTP HOOGVLIET

To allow for the sampling of a wider range of future scenarios, conceptual models have to be used. Here, the following methodology is applied to the case study of WWTP Hoogvliet. For details, please refer back to Chapter 3.3.2, where this case study is presented in detail. Conceptual models used in urban drainage modelling are often virtual-reservoir models (Cembrano, 2004), but other forms of simplified models could be used (e.g. Dobson et al. (2022) and Meijer et al. (2018)), provided they incorporate a physical-based description of the UDS and its structure. This means an encoding of the effective surface area, UDS storage capacity and pumping capacities (if appropriate). Here, the virtual-reservoir model was used, as the speed-up increased computational efficiency obtained this way allows for more simulations to be performed. Using this simplified model, the UDS is partitioned using the same graph partitioning algorithm used for the detailed transition analysis.

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

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

This trade-off also makes the stochastic urban transitions practically only applicable to evaluate heuristic control procedures, as real-time optimisation would be too time-consuming. However, one or more links in the chain, which show divergence in the RTC performance, can be assessed to gain an understanding of the differences between heuristic and real-time optimisation control.

The set of rainfall events can include climate change projection, in order to assess the continued potential of RTC procedures under long-term, climate-related changes to the precipitation patterns. As the influence of climate change was assessed in previous work (Dirckx et al., 2017), this transition is omitted from this work, allowing a more detailed focus on the transitions which have not been studied before.

Three scenarios were set up to test within the stochastic framework: Scenario 1 following unbiased transitions, Scenario 2 following biased densification and Scenario 3 following biased SUDS implementation. The *unbiased transitions* scenario follows an equal probability implementation of densification and BG infrastructure within each catchment; *biased densification* has a proclivity for densification, and *biased SUDS* has a proclivity for BG infrastructure implementation. Each follows a set of transition probabilities at each step in the chain which is independent of previous states (8.1), forming the basis of the used MCMC framework. The densification and BG infrastructure implementation here follows a randomly sampled value per catchment (independent of the change applied to the other catchments) in the UDS from a normal distribution for the transition probability. To have a sufficiently wide range of changes staying within the planned or historically observed changes, normal distributions with a mean of 3% or and standard deviation of 1% were used for Scenario 1, and a mean of 6% with a standard deviation of 2% for Scenarios 2 and 3 (either growth or shrinkage).

Table 8.1: Transition probabilities per parameter and scenario

Scenario	**SWMM Parameter**	**Units**	**Transition Cause**	**Growth Distribution**
Scenario 1 - Unbiased Transitions	Subcatchment imperviousness	%	Urban growth leading to densification	$\mathcal{N}(3,1)$
	Subcatchment imperviousness	%	Implementation of SUDS	$\mathcal{N}(3,1)$
Scenario 2 - Biased Densification	Subcatchment imperviousness	%	Urban growth leading to densification	$\mathcal{N}(6,2)$
Scenario 3 - Biased SUDS	Subcatchment imperviousness	%	Implementation of SUDS	$\mathcal{N}(-6,2)$

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

The runs were done following the heuristic RTC procedure which was developed as part of the CAS2.0 project, which is further expanded on in Chapter 3. Furthermore, a GA-based MPC procedure was also used for a targetted analysis of one of the links of the MCMC. The details of this procedure can be found in Chapter 5. The GA-based MPC was selected above the LP-based MPC to minimise the differences between the different case studies (as the MPC for the Eindhoven case study was exclusively based on a genetic algorithm given the highly non-linear behaviour of the transport system.

The same radar rainfall data source as described in the case of the detailed transition was used. Different events were selected though. 9 events recorded between 2019 and 2021 were used with total rainfall depths of 14.82-22.4 mm ranging from a mean depth of 18.24 mm, and maximum intensity ranging from 5.48 to 30.76 mm/hr. For the MPC runs, the observed rainfall data was used as the rainfall prediction as well, to minimise potential impacts of uncertainties on the final outcome. This allows for a better analysis of the impact of the transitions on the performance of RTC.

8.2. RESULTS AND DISCUSSION

This section sets out and discusses the results obtained through the aforementioned methodology. First, the results for the WWTP Eindhoven (Riool-Zuid, upstream of PS Aalst) catchment, following the detailed transitions framework, are presented and discussed. At the end of the section, the WWTP Hoogvliet, following stochastic transitions, case study results are presented.

8.2.1. DETAILED URBAN TRANSITIONS - EINDHOVEN

Given the transitions described in Section 8.1.1, a net increase in CSO volume compared to the current, non-transitioned UDS was observed for Scenarios 1 (an increase of the total effective catchment size over the entire UDS) and 4 (increase in UDS Sections 1 and 2 of the case study, decrease in UDS Section 2 of the effective catchment size). Conversely, a total CSO volume decrease was observed for the other two scenarios, in line with the total effective catchment size of the UDS (Figure 8.4). The performance ranking of the three, unchanged RTC approaches (simple heuristics, advanced heuristics and MPC-based) remained constant throughout all the scenarios.

Considering the normalised CSO value for each scenario, no clear trends could be identified (Table 8.2). All control procedures remained relatively stable, indicating a near-linear correlation between the CSO reduction and the runoff reduction for the studied events, with no difference in dynamics found between the control producers. On the other hand, considering the relative CSO performance, a larger range in relative performance can be observed for the heuristic control (1.93-4.09) compared to the advanced heuristic (1.58-3.34) and MPC (1.44-2.98) procedures. Therefore, for this catchment, the simplest form of control (single input single output heuristics) is most sensitive to changes in the urban drainage system and catchment with the highest relative perfor-

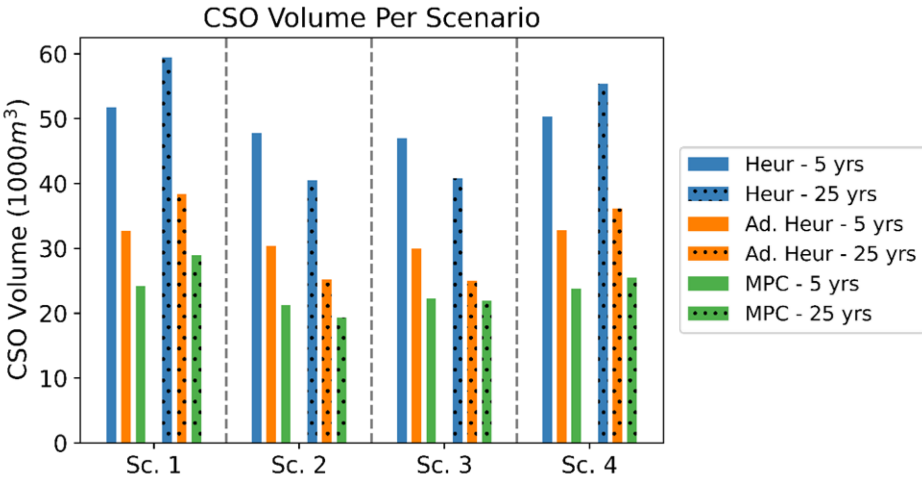


Figure 8.4: Total CSO volumes for detailed transition scenarios, RTC approaches and projection horizons

mance loss as it was the least able to materialise the RTC potential.

Table 8.2: Results of the detailed urban transitions

Scenario	**Transition Year**	**Normalised CSO Volume**			**Relative CSO Volume**		
		Heur.	**Adv. Heur.**	**MPC**	**Heur.**	**Adv. Heur.**	**MPC**
Scenario 1	5	0.032	0.027	0.025	2.15	1.77	1.64
	25	0.034	0.026	0.025	2.03	1.66	1.54
Scenario 2	5	0.033	0.022	0.020	3.39	2.72	2.06
	25	0.031	0.022	0.020	4.09	3.34	2.98
Scenario 3	5	0.031	0.025	0.023	2.35	1.89	1.59
	25	0.026	0.022	0.020	3.69	3.09	2.74
Scenario 4	5	0.032	0.027	0.022	2.13	1.77	1.58
	25	0.032	0.026	0.022	1.93	1.58	1.44

Considering the aforementioned change in the relative CSOs, the relation of these with the change in total generated runoff volume ($\Delta V = (V_{new} - V)/V_{old} * 100$) was investigated (Figure 8.5). Although no clear one-to-one relation between the total runoff change and the relative CSO volume could be observed, a negative correlation between the runoff change and relative CSO volume seems to arise, although no change with an increased runoff can be observed. Only considering the total runoff change is insufficient given the heterogeneous implementation of the runoff change for scenarios 2 and 3. Especially the 25-year implementation of Scenario 3 (the data points highlighted in Figure 8.5), shows that total runoff change by itself does not sufficiently explain the variance in relative performance. However, additional data points are necessary to adequately distil the relations dictating the change in relative CSO volume.

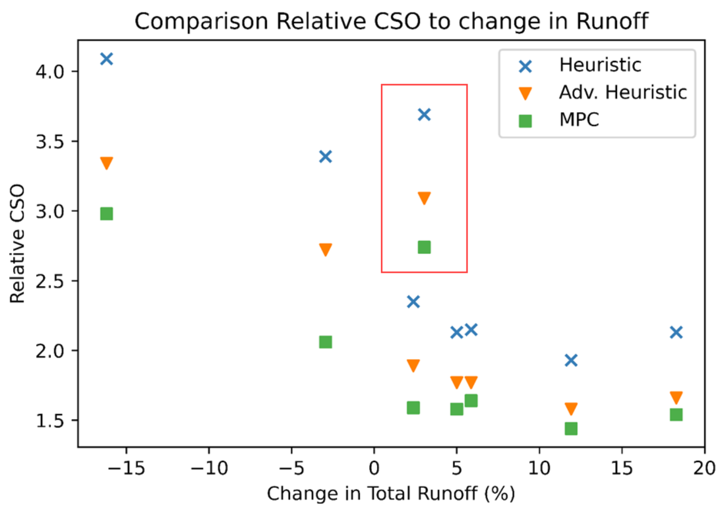


Figure 8.5: Difference in the relative CSO change to runoff change per control procedure

Computing the comparative CSO volume (the total CSO volume for each scenario divided by the total CSO volume of the current UDS configuration for all three procedures), again no trend can be observed highlighting different levels of sensitivity to gradual changes occurring in the UDS between the three studied RTC approaches (Figure 8.6). MPC-based RTC approaches have been found to be relatively resilient against rainfall nowcast uncertainty (Fiorelli et al., 2013), see also Chapter 6 and therefore indirectly to uncertainties in the rainfall-runoff module of the internal-MPC model (the part of the UDS that was changed here). The validity of the optimisation method was checked by ensuring that the objective function achieved had levelled off completely and ensuring that the computational time to find the optimum was below the sampling period (5 minutes for the Eindhoven catchment).

8.2.2. STOCHASTIC URBAN TRANSITIONS - HOOGVLIET

The impact of the urban transitions associated with the three scenarios on the total CSO volume was assessed for the WWTP Hoogvliet case study using an optimised heuristic control, on the total CSO volume was assessed. As the effective catchment size increases or decreases, the total CSO volume follows the same trend, as shown in Figure 8.7a. Similarly, the normalised CSO volume increases as the total CSO volume increases (Figure 8.7b). However, based on the relative performance, an opposite trend can be seen: there is a decreasing trend in relative CSO discharge associated with the increased effective

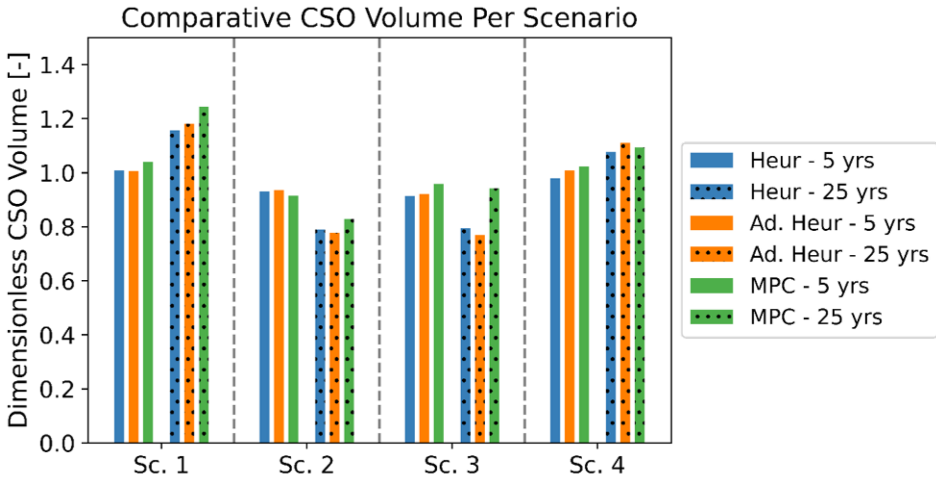
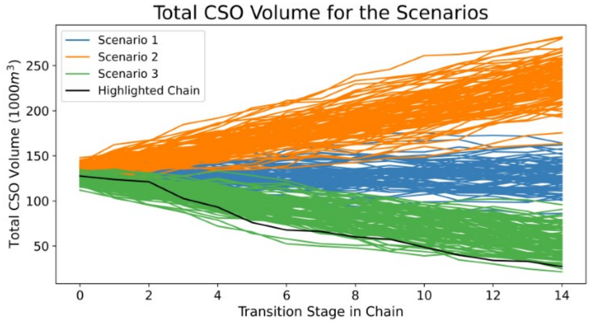


Figure 8.6: Ratio of the total CSO volume and the baseline CSO per event. No clear sensitivity between control types could be observed

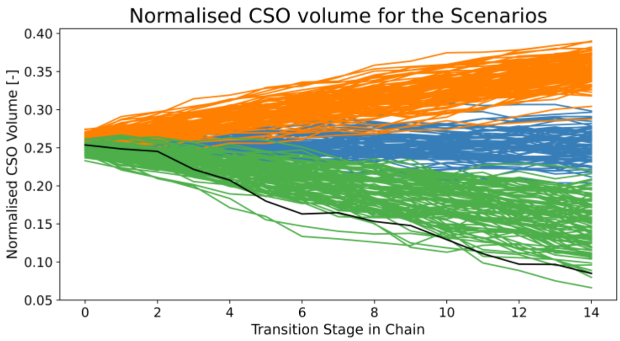
catchment size (Figure 8.7c, note the difference in scale of the y-axes). Moreover, there is an increase of up to a factor of 40 in the relative CSO observed for Scenario 3 (biased SUDS). This indicates that the heuristic control procedure is unable to achieve the full RTC potential. This further highlights the need to consider all three metrics proposed here to gain a better understanding of the need for re-evaluating the control procedure. To further investigate the dynamics between a transitioning urban environment and the control procedure, one of the chains from stochastic Scenario 3 was selected for further analysis. The chain highlighted (Figure 8.7, Scenario 3) was selected as it showed one of the highest changes in total CSO volume and normalised CSO volume, yet more median relative performance, making it an interesting set of transitions to analyse.

8

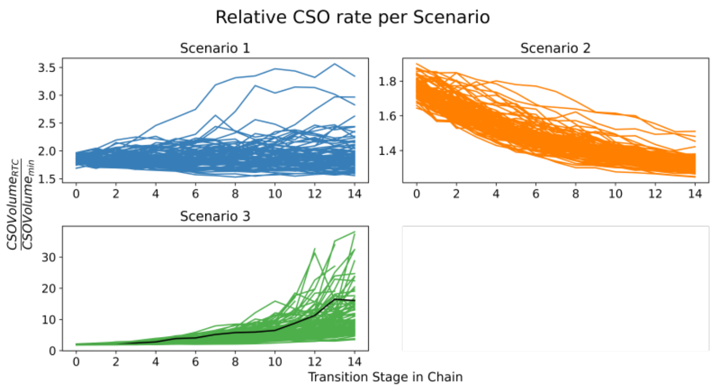
The relationship with the percentage relative change in total generated runoff volume ($\Delta V = (V_{new} - V_{old})/V_{old} * 100$) was investigated. A downward logarithmic relation between the relative CSO rate and the total runoff change was observed. As ΔV approaches -100% (meaning no runoff is generated and routed towards the UDS but rather captured or diverted by the implemented BG infrastructure), the minimum CSO rate (the maximum RTC performance) will reach 0. The above indicator, in that scenario, is no longer useful, as the relative CSO rate goes to ∞ (as in theory all CSO events could have been negated). This can be seen in Figure 8.8, where the relation between the relative CSO rate and percentage runoff change becomes asymptotic around a 50% reduction in the total runoff on the left side of the figure. For the re-evaluation of the control rules, there is no clear breakpoint or threshold which can be identified as there is a relatively constant acceleration (similar to static hydrological impacts of urbanisation as reported by Booth and Jackson (1997)). Around -15% total runoff change, however, the relative CSO rate exceeds 2.5 and starts to rapidly increase which would indicate a good point for re-evaluation. The logarithmic relationship does suggest that frequent



(a)



(b)



(c)

Figure 8.7: (a) total CSO volume, (b) normalised CSO volume and (c) Dimensionless Overflow rate per chain in each scenario

re-evaluation of heuristic control policies is recommended.

The performance of the highlighted chain from Scenario 3 (see Figure 8.7 and Figure

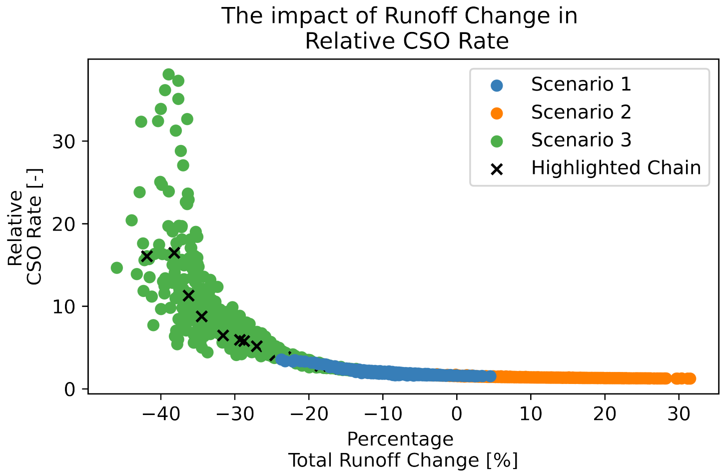


Figure 8.8: Assessment of the relation between percentage total runoff change and relative CSO rate, based on 3 scenarios including 100 chains, with fourteen links at 8 events per link

8.8) was further assessed to gain a better understanding of the performance of the various control procedures. Two MPC models were run to assess the importance of model recalibration: (1) using the original model (where no urban transitions were applied) and (2) using the model representing the transitioned state of the UDS as the internal MPC mode respectively, thus showing the RTC performance with and without recalibration of the internal MPC model. These two MPC implementations were compared to the original heuristic procedure (without re-optimising the rules). The analysis was conducted for the same set of rainfall events as were used to assess the heuristic longevity (see Section 8.1.1 for details).

The total CSO volumes were caused exclusively by the pumped CSOs. However, the extent of the CSO volume varies significantly (Figure 8.9). The adjusted MPC performs the best with a total CSO volume of 17,519 m^3 (9.77 mm), followed by the heuristic control with a total CSO volume of 21,213 m^3 (11.83 mm) and finally the original MPC with a total CSO volume of 24,219 m^3 (13.51 mm). This means that the non-adjusted heuristic control outperformed the non-adjusted MPC procedure (Figure 8.9), which is the opposite of the sensitivity per procedure observed for the Eindhoven case study. Repeated re-evaluation of the performance of the internal MPC model used should be prioritised to maintain the long-term optimality of the MPC strategy. Continuous assessment of the predictive performance of the internal MPC model and its automatic recalibration (expanding on the work presented by Kroll et al. (2017)) should therefore be an integral part of the implementation of MPC strategies.

This opposite level of sensitivity to change per procedure compared to the Eindhoven case study suggests a high level of case study specificity. This comparative difference in sensitivity is likely due to the nature of the heuristic control, where the Eindhoven case study relied on set points in the form of a set flow rate. The difference in performance

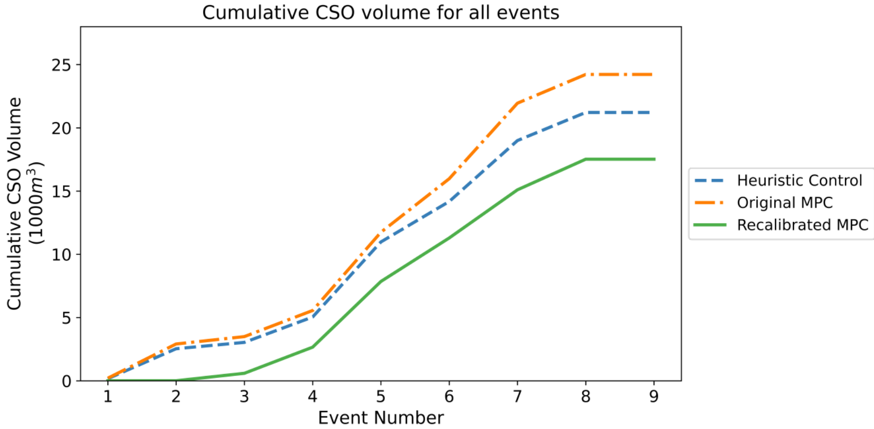


Figure 8.9: A comparison between the original MPC, recalibrated MPC and heuristic control for the final link in the highlighted chain (see Section 8.1.1 for rainfall details)

for the WWTP Hoogvliet case as shown in Figure 8.9 is exclusively due to the pumped CSOs. The cause for the relative increase compared to the heuristic control is due to an overestimation in the runoff leading to the optimal setting calculated including the pre-emptive switching on of the pumped CSOs. This loss induced through the rainfall-runoff section of the internal MPC model is in apparent contrast with earlier findings of low levels of sensitivity to rainfall forecast uncertainty for MPC highlighted in Chapter 6. As the pumped CSOs cause overflows immediately when switched on, the self-adjusting properties of MPC (which are the cause for the low impact of rainfall forecast uncertainty on the performance of MPC methods) are less pronounced. Additionally, a relatively low frequency of set point updating (15 minutes due to physical constraints in the UDS) decreases the self-adjusting potential of the MPC scheme further.

8

8.2.3. DISCUSSION

One of the key points highlighted by looking at the two case studies is the necessity to re-evaluate the applied RTC strategy when large-scale transitions occur in the urban environment, a time-scale previously not considered in the review by Mollerup et al. (2017). This would require a shift in the current control paradigm, where the aim is to optimise a UDS in its current state as opposed to keeping the long-term changes in mind. Exploratory modelling techniques aimed at assessing possible pathways for urban water transitions (e.g. Duque et al. (2022)) should explicitly consider the role of RTC as a means of accommodating these future transitions and the potential impacts the transitions may have on the performance potential of the corresponding RTC procedures.

Formal optimisation techniques for network rehabilitation or BG infrastructure implementation (e.g. Fiorillo et al. (2022)) should also consider these interactions. Given the rise of Digital-Twins in practice in the urban drainage community (Pedersen et al., 2021b), incorporating an automated version of the methodology presented here could allow for more effective long-term implementation of the RTC strategies and procedures. Furthermore, given the relative sensitivity of MPC-based RTC procedures to the transitions modelled here, future research into continuous data assimilation for the internal MPC model, similar to what is currently done for other hydraulic models (e.g. Milašinović et al. (2022)) and for non-transitioning UDS (Hutton et al., 2014; Vermuyten et al., 2018), is recommended. The influence of data uncertainty, and predominately observed rainfall, might make the continuous data assimilation method difficult. Communication between the responsible parties for both the urban environment and the UDS operator should therefore be strengthened. The analysis done by Manny (2023) on the UDS as a socio-technical system can be used for the identification of possible bottlenecks in this context.

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

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

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

Furthermore, the rainfall depth of various events was near the threshold of CSO occurrence, with the total rainfall volume being close to the combined static and dynamic capacity of the UDS. The effect of the transitions of the (relative) performance of RTC was assumed highest for these events, as these are the events which have the highest level of RTC potential (Vezzaro, 2022). No clear relation between the change in performance of the RTC and the rainfall depth was found within either of the datasets. This, in combination with the aforementioned apparent resilience against smaller UDS changes, was surprising as RTC procedures are designed and optimised to function as close to the UDS capacity as possible. This drift from optimality is clearly visible only when significant changes in urban permeability are realised, predominately due to the implementation of blue-green infrastructure.

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

One of the shortcomings of this work is that it only assessed the impact of cumulative small configurational changes on the longevity of RTC strategies. During the operation of the RTC procedure, major changes to the existing infrastructure, driven by changing regulations in the wastewater domain, are likely to occur. This will lead to the need to re-evaluate RTC strategies more frequently than recommended here. This does further highlight the need to consider changes to the UDS within the planning phase of the RTC to achieve longevity.

8.3. CONCLUSIONS AND FUTURE OUTLOOK

This chapter presents a methodology for assessing the longevity of Real-Time Control (RTC) procedures in urban drainage systems (UDS). The new methodology was applied to two catchments in the Netherlands. The following transitional changes to the urban areas were studied: (1) densification of the existing catchments and (2) implementation of blue-green (BG) infrastructure. These changes were studied based on a detailed representation of the UDS using deviant case sampling methods, and a simplified representation of the UDS using stochastic sampling strategies. Both heuristic and model predictive control (MPC) based RTC procedures were evaluated. The performance of different RTC procedures under the modelled transitions was studied.

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

- The transitional changes in the analysed urban areas start becoming significant, i.e. impacting the performance of UDS RTC procedures (both heuristic and MPC) only when changes to the total generated runoff reach approximately 15% or more.

The impact is measured using both a measure of achieved RTC potential and RTC performance. This indicates a relatively high inherent longevity of both MPC and heuristic control procedures considering relatively slow transitions occurring in the urban environment;

- Regarding the relative sensitivities of heuristic and MPC-based control procedures, the results differed between the two case studies. Therefore, no generalized statements about the relative sensitivities of different RTC procedures could be made. The impacts of urban transitions should therefore be assessed separately for each UDS where RTC is currently implemented. In the WWTP Hoogvliet case studies, the long-term performance of real-time optimization started to perform worse compared to the baseline heuristic method.

- To ensure the longevity of advanced RTC procedures, continuous monitoring of the performance of all control strategies is needed. This can avoid a loss in RTC performance in practice through the identification of performance loss. Good communication between relevant stakeholders on both the urban design and operation sides should therefore a key component in RTC implementation;

- • Using the total CSO volume alone is not sufficient to assess the long-term performance of an urban drainage system operated through a volume-based control procedure. Volume rates alone do not provide sufficient insights into the change in RTC potential caused by urban transitions. Therefore, an additional metric based on the difference between the performance of the RTC strategy and the maximum RTC potential (see Chapter 4) is needed to make informed decisions on the frequency of re-evaluations of the RTC procedure;

- A negative logarithmic relation between the reduction in total generated runoff and the relative RTC performance, measured by the aforementioned difference between RTC performance and maximum performance potential, was found for a heuristic RTC procedure implemented in the WWTP Hoogvliet case study. This increasing performance loss when BG infrastructure is implemented on a large scale indicates the need to re-evaluate the underlying rules for heuristic control policies. Failing to account for urban transitions would negate part of the gains made via BG infrastructure implementation;

- Re-evaluation (ensuring that the model is well-calibrated and representative of current UDS dynamics) of the internal MPC model can significantly improve the long-term performance of the RTC procedure. Automated data assimilation methods should therefore be included in future implementations of MPC procedures. This non-stationary approach to RTC could be a strategy to accommodate urban transitions without the need for additional investments.

The conclusions presented here hold for the two case studies (WWTP Hoogvliet and Riool-Zuid). Given the site-specific nature of the results, more case studies are necessary to predict correlations between urban transitions and their impact on RTC performance. Aside from this. future research directions should include additional transitions in the

UDS, such as the ubiquitous implementation of separate sewer systems and changes to the (requirements of the) wastewater treatment plant. Especially changes to the underground infrastructure itself, or combined transitions, should be investigated. Furthermore, incorporating data assimilation techniques and automatic maintenance of full-hydrodynamic models in the continuous assessment framework should be prioritized to ensure the continued optimal performance of RTC procedures.

9
CONCLUSION AND FUTURE OUTLOOK

THIS thesis aims to enhance the understanding of the effects of uncertainty on the efficacy of real-time control (RTC) strategies applied to urban drainage systems (UDS) for the reduction of combined sewer overflow (CSO) volumes. In previous chapters, a performance indicator and a novel control algorithm were developed, followed by an in-depth look at the effects of rainfall, model and boundary condition uncertainties on the performance of heuristic and real-time optimisation-based control procedures. These methodologies are applied to three UDS connected to three different wastewater treatment plants (WWTPs).

This chapter presents the main conclusions drawn throughout the work presented in this thesis. These conclusions are followed by practical implications of the results and an outlook on future research directions. The conclusions are synthesised from the conclusions per chapter, where more detailed conclusions can be found.

9.1. CONCLUSIONS

1 - The maximum achievable performance potential and a minimum performance baseline can give better insights into the functioning of an RTC strategy applied to UDS. Chapter 2 showed that conclusions related to RTC efficacy cannot be drawn from literature as there is no standardised method for reporting the functioning of RTC procedures. Computing the minimum baseline ensures that the performance improvement through RTC is attributable only to the quality of the RTC procedure rather than the underperformance of the system in the pre-RTC functioning. The presence of this underperformance could otherwise bias the results significantly. Similarly, understanding the maximum potential for operational optimisation can scale the RTC efficacy based on the physical layout of the UDS, making the comparison of RTC efficacies between different UDS possible.

2 - Model and dynamic system capacity uncertainties can cause a real-time optimisation procedure to be outperformed by a statically optimised heuristic controller. The influence of rainfall forecast, model and dynamic boundary condition uncertainty on the efficacy of model predictive control (MPC), was found to vary significantly. Although rainfall forecast uncertainty showed a negligible influence on the final RTC performance, both model uncertainty and boundary condition uncertainty showed a risk of a performance decrease compared to the perfect scenario and, in some cases, the heuristic baseline. Two forms of risk could therefore be identified: a risk of operative deterioration (worse performance compared to lower baseline) and a risk of relative system performance loss (worse compared to the perfect information (no uncertainty) situation).

3 - Rainfall forecast uncertainty affects the performance of heuristic control procedures more compared to real-time optimisation procedures. When augmenting a heuristic control procedure with rainfall forecasts, the rainfall characteristics that the heuristic procedure relies on can have a significant influence on the practical efficacy of the nowcast-informed heuristic control strategy. Particularly the ability of nowcast algorithms to predict the end of a rainfall event has shown potential for the improvement of the performance of heuristic RTC strategies with limited risks. On the other hand, depth and exceedance prediction of rainfall showed a high potential to increase the performance of the nowcast-informed procedure, but pose a high risk of performance loss when using real forecasts. Rainfall statistics can be used to directly infer if a procedure has real potential in practice, as they are strongly correlated to the associated risks, although quantification of the risk through rainfall prediction statistics alone was not possible. Heuristic control algorithms appear to be more sensitive to uncertain rainfall forecasts compared to real-time optimisation procedures.

4 - Long term changes have the greatest impact on the performance potential of RTC procedures, less so on the performance itself. Urban transitions are applied to two case studies and both heuristic and MPC control procedures are tested to see if they're affected by either densification of the urban area or a widespread implementation of blue-green (BG) infrastructure. When BG infrastructure was added to the model, the relative performance of the RTC decreased exponentially and some real performance loss was found for MPC procedures. No consistency amongst the studied catchments in susceptibility regarding the type of RTC procedure was found, with an MPC procedure being impacted less compared to a heuristic procedure for one catchment and more for the other. Local assessments of the impacts are therefore necessary to ensure optimal control. In the case of MPC, re-evaluation of the internal-MPC model should be done with some frequency (dependent on the changes occurring in the system) to ensure that performance does not perform worse compared to a heuristic control strategy.

To conclude, uncertainties can have a significant effect on the efficacy of both heuristic and real-time optimisation control procedures. The extent of the influence depends on the case study but can lead to the operation of the UDS being below worse (increasing the total overflow volume) compared to a static form of control. These uncertainties can be exacerbated over time through continuous development of the urban area, influencing both the RTC efficacy and the RTC potential.

9.2. PRACTICAL IMPLICATIONS

The results presented here should be seen in the context of increased implementation of more advanced control strategies, pushed by digitalisation, cheaper sensor and communication networks and increased environmental awareness (leading to more stringent legislation). In this section, the main results are placed within a practical context to synthesise practical advice to practitioners in the field of UDS operation.

1 - Uncertainties should always be considered during the design stage of a real-time control strategy. Given the shown potential impact of uncertainties on the efficacy of both heuristic and real-time optimisation procedures, accounting for these uncertainties when implementing a control strategy is a necessity. Understanding the magnitudes of the performance reduction related to each source of uncertainty is necessary prior to RTC implementation. However, when these uncertainties are understood sufficiently, they can be mitigated within the control architecture. Real-time optimisation can therefore already be implemented more ubiquitously with limited adjustments to the current design paradigm.

2 - Long-term functioning concerns should not be a barrier against the implementation of real-time control. Indicated by the results presented in Chapter 8, the impact of long-term transitions is unlikely to yield performance losses over small time horizons (several years to decades). It should be noted, however, that significant losses in the performance of the MPC started occurring after a 15% change in the total runoff, meaning that the recalibration of internal MPC models should be part of the standard implementation of MPC procedures. Ideally, this is paired with continuous assessment of the function of the RTC efficacy using rainfall, monitoring and modelling data to assess the functioning of the RTC procedure.

3 - Real-time optimisation procedures are best implemented in a step-wise manner, increasing the complexity over time. Given the decreasing magnitude of performance improvement with more complex real-time optimisation methods, starting with heuristic forms of control and developing upon those (through the inclusion of forecast, or hybrid forms of control) is recommended. This way, a balance between UDS optimisation and risk reduction through a better understanding of the control performance is made. The performance loss through uncertainty will likely be minimal when following this form of approach. Additionally, it allows operators to tweak and get accustomed to the (semi-) automated form of real-time control.

4 - Including rainfall forecasts in heuristic control should be preceded by the screening of the accuracy of the forecasted rainfall properties. Significant risks can be associated with these uncertainties in a heuristic setting. The impact of these risks should, on a case-by-case basis, be weighted and operators should make decisions on how to improve the operation of the UDS based on a thorough analysis of the system function in relation to the various uncertainties present.

9.3. FUTURE RESEARCH

Although the research presented in this thesis has given some insights into the influence of various uncertainties on the performance of different real-time control procedures, additional research is recommended. Below, several research lines are outlined.

1 - The application of the methodologies presented should be applied to additional case studies to assess the transferability of the conclusions or gain additional insights. Especially the methodology developed in Chapter 6, used to determine the influence of various sources of uncertainty on the efficacy of MPC, should be tested on more catchments to further validate and gain additional understanding of the uncertainty and real-time control efficacy dynamics. Furthermore, the integration of more sources of uncertainty (such the monitoring values (used as the initial conditions in the internal-MPC model)), should be studied, as well as a more detailed breakdown of the model uncertainty and risk of performance loss.

2 - The formal application of propagation of uncertainty theory should be compared to the more empirical results provided here. Taking a more formal mathematical approach, as opposed to the empirical modelling experiments presented here, might yield additional insights. This would require a better understanding of the theoretical interactions between the optimisation algorithms, the search space and the uncertainties related to both. Comparing a theoretical framework to the empirical framework presented here would yield a better understanding of both the underlying mathematical implications and the potential influence of uncertainties not yet assessed here.

3 - The influence of uncertainties should be assessed within the context of the HAPPy algorithm developed here. Given the increased reliance on monitoring values and rainfall predictions (for initial conditions of the internal-MPC model *and* the dynamic prediction of the most influential actuators), the influence is likely to be larger compared to those of 'traditional' MPC procedures. Understanding how these uncertainties propagate within the HAPPy framework is a key step to ensuring the implementability of the procedure.

4 - Development of a rigorous methodology to assess the impact of uncertainties using a data-driven approach. In an ideal situation, comprehensive data sets of UDS which are controlled through an automated MPC procedure should be made available. Combining data-driven and model-based performance assessments can give more confidence in the final conclusions drawn and could make an interesting comparative study of the theoretical and practical influence of uncertainties. The availability of such data sets is also a key step in the more ubiquitous implementation of MPC systems in practice, as they can prove the practical functioning of these control procedures to practitioners. To this effect, a sequential methodology for MPC implementation (starting with heuristic, then nowcast-informed heuristics, followed by hybrid heuristic and real-time optimisation ending in a full MPC system) should be developed and implemented. Understanding the relationship between both model and optimisation complexity and RTC performance is a key step needed to achieve this.

5 - A formal methodology for the improvement of heuristic control using nowcast data should be developed based on the findings presented in Chapter 7. Finding a one-size fit all methodology for the development of improved heuristic control could be a good augmentation to existing methodologies used for the simplified design of control strategies. A better understanding of the trade-offs of complexity is necessary as well as a more comprehensive set of rainfall-related statistics.

6 - The methodologies presented here should be adjusted to accommodate pollution and impact-based control objectives. Further integration of wastewater treatment processes within the control strategy to assess the effect of uncertainties in an integrated manner should also be prioritised in future research. These types of real-time control, given more attention in the early 2000s, are likely to become increasingly sought after given the legislation going towards an impact-based form rather than strict limits on emissions. Given the additional uncertainties within the models needed for these forms of control, however, an increased impact on the performance of the real-time control strategy can be expected. Comparing the potential risks emerging from these additional uncertainties with the potential benefits is a key understanding necessary when deciding on the type of real-time control to be designed and implemented.

A

DETAILS ON HEURISTIC CONTROL OF THE EINDHOVEN CASE STUDY

The set points used in the development of the Realised Potential Indicators, applied to the two control stations in Riool-Zuid catchment are shown. These are the set points dependent on the system state, the definition of which can be found in Chapter 4. The values below are optimised using a genetic algorithm, with the search boundary set for to 3,000-7,000 and 1750-3500 m^3h^{-1} for CS De Meeren and Valkenswaard respectively. Intervals of 250 m^3h^{-1} were used. In the first two tables (Tables A.1 and A.2), the control settings for Strategy 1 (see Chapter 4) is described, followed by the table detailing Strategy 2 per PS Aalst performance interval.

Table A.1: Set points for Control Station De Meeren per upstream and downstream flow phase. All values are in m^3h^{-1}.

		Downstream				
		Filling	**Spilling**	**Stable**	**Emptying**	**DWF**
Upstream	**Filling**	6000	4000	5500	6500	U*
	Spilling	6500	5000	6500	7000	U*
	Stable	5000	4500	5000	6500	U*
	Emptying	4500	4000	5000	6750	U*
	DWF	3000**	3000**	3000**	3000**	U*

**Unrestricted flow through the control station*
*** Although these is a values for this, DWF flow is below 3000 m3/h and therefore no real restriction occurs.*

A

Table A.2: Set points for Control Station De Valkenswaard per upstream and downstream flow phase. All values are in $m^3 h^{-1}$.

		Downstream				
		Filling	**Spilling**	**Stable**	**Emptying**	**DWF**
Upstream	**Filling**	2750	2250	2750	2750	U*
	Spilling	3250	2500	3250	3250	U*
	Stable	2500	2000	2500	2750	U*
	Emptying	2250	1750	2500	2750	U*
	DWF	1500**	1500**	1500**	1500**	U*

**Unrestricted flow through the control station*
*** Although these is a values for this, DWF flow is below 3000 m3/h and therefore no real restriction occurs.*

Table A.3: Set points for Control Station De Meeren per upstream and downstream flow phase if PS Aalst delivers 7,000-8,000 $m^3 h^{-1}$. All values are in $m^3 h^{-1}$.

		Downstream				
		Filling	**Spilling**	**Stable**	**Emptying**	**DWF**
Upstream	**Filling**	5500	4000	5000	6000	U*
	Spilling	6250	4500	6250	6500	U*
	Stable	5000	4500	4500	6500	U*
	Emptying	4000	4000	4500	6000	U*
	DWF	3000**	3000**	3000**	3000**	U*

**Unrestricted flow through the control station*
*** Although these is a values for this, DWF flow is below 3000 m3/h and therefore no real restriction occurs.*

Table A.4: Set points for Control Station De Meeren per upstream and downstream flow phase if PS Aalst delivers 8,000-9,000 $m^3 h^{-1}$. All values are in $m^3 h^{-1}$.

		Downstream				
		Filling	**Spilling**	**Stable**	**Emptying**	**DWF**
Upstream	**Filling**	6000	4000	5500	6500	U*
	Spilling	6500	5500	6500	7000	U*
	Stable	6000	4500	5000	7000	U*
	Emptying	4500	4000	5000	6750	U*
	DWF	3000**	3000**	3000**	3000**	U*

**Unrestricted flow through the control station*
*** Although these is a values for this, DWF flow is below 3000 m3/h and therefore no real restriction occurs.*

Table A.5: Set points for Control Station De Meeren per upstream and downstream flow phase if PS Aalst delivers 9,000-10,000 m^3h^{-1}. All values are in m^3h^{-1}.

		Downstream				
		Filling	**Spilling**	**Stable**	**Emptying**	**DWF**
Upstream	**Filling**	6500	4000	5500	6750	U*
	Spilling	7000	6500	7000	7500	U*
	Stable	6250	4750	6250	7250	U*
	Emptying	5000	4000	5500	7250	U*
	DWF	3000**	3000**	3000**	3000**	U*

**Unrestricted flow through the control station*
*** Although these is a values for this, DWF flow is below 3000 m3/h and therefore no real restriction occurs.*

Table A.6: Set points for Control Station Valkenswaard per upstream and downstream flow phase if PS Aalst delivers 7,000-8,000 m^3h^{-1}. All values are in m^3h^{-1}.

		Downstream				
		Filling	**Spilling**	**Stable**	**Emptying**	**DWF**
Upstream	**Filling**	2500	2000	2750	2500	U*
	Spilling	2750	2500	2750	3000	U*
	Stable	2500	1750	2500	2750	U*
	Emptying	2250	1750	2500	2500	U*
	DWF	1500**	1500**	3000**	1500**	U*

**Unrestricted flow through the control station*
*** Although these is a values for this, DWF flow is below 3000 m3/h and therefore no real restriction occurs.*

Table A.7: Set points for Control Station Valkenswaard per upstream and downstream flow phase if PS Aalst delivers 8,000-9,000 m^3h^{-1}. All values are in m^3h^{-1}.

		Downstream				
		Filling	**Spilling**	**Stable**	**Emptying**	**DWF**
Upstream	**Filling**	2750	2250	2750	2750	U*
	Spilling	3000	2750	3000	3000	U*
	Stable	2500	2000	2750	2750	U*
	Emptying	2250	1750	2500	2750	U*
	DWF	1500**	1500**	3000**	1500**	U*

**Unrestricted flow through the control station*
*** Although these is a values for this, DWF flow is below 3000 m3/h and therefore no real restriction occurs.*

A

Table A.8: Set points for Control Station Valkenswaard per upstream and downstream flow phase if PS Aalst delivers 9,000-10,000 $m^3 h^{-1}$. All values are in $m^3 h^{-1}$.

		Downstream				
		Filling	**Spilling**	**Stable**	**Emptying**	**DWF**
Upstream	**Filling**	3000	2250	3000	2750	U*
	Spilling	3250	3000	3250	3250	U*
	Stable	2750	2000	3000	3000	U*
	Emptying	2500	1750	2500	3250	U*
	DWF	1500**	1500**	3000**	1500**	U*

**Unrestricted flow through the control station*
*** Although these is a values for this, DWF flow is below 3000 m3/h and therefore no real restriction occurs.*

B

ADDITIONAL DETAILS ON THE HAPPY PROCEDURE

Some additional details used for the development of the HAPPy are detailed here. First, in Table B.1 and B.2, the rainfall details can be found for WWTP Dokhaven and WWTP Hoogvliet respectively. This is followed by the details of the convergence time dependent on the number of actuators used in the procedure (for the WWTP Dokhaven case study) and then a detailed breakdown of one of the events.

B.1. RAINFALL DETAILS

Here, the rainfall details per event ID are shown, considering the total depth, duration and maximum intensity over the entire catchment.

Table B.1: Rainfall details for the runs done for the WWTP Dokhaven analyses

Event Number	Total Depth (mm)	Duration (hours)	Max. Intensity (mm/hr)
1	8.17	3.28	16.4
2	19.7	9.54	15.3
3	22.9	11.9	8.94
4	33.2	9.24	52.3
5	6.77	3.83	6.75
6	15.4	6.31	13.9
7	20.6	9.83	17.2

Table B.2: Rainfall details for the runs done for the WWTP Hoogvliet analyses

Event Number	Total Depth (mm)	Duration (hours)	Max. Intensity (mm/hr)
1	25.8	9.00	12.1
2	22.3	7.75	10.9
3	25.1	10.5	24.7
4	26.5	11.0	18.6
5	28.0	7.25	30.7
6	42.6	9.25	19.3
7	14.9	5.25	17.2

B

B.2. COMPUTATIONAL TIME

Figure B.1 shows the distribution of the time it took for the algorithm to converge to an optimal setting (from the starting moment, therefore including the simplification and generation of the simplified model).

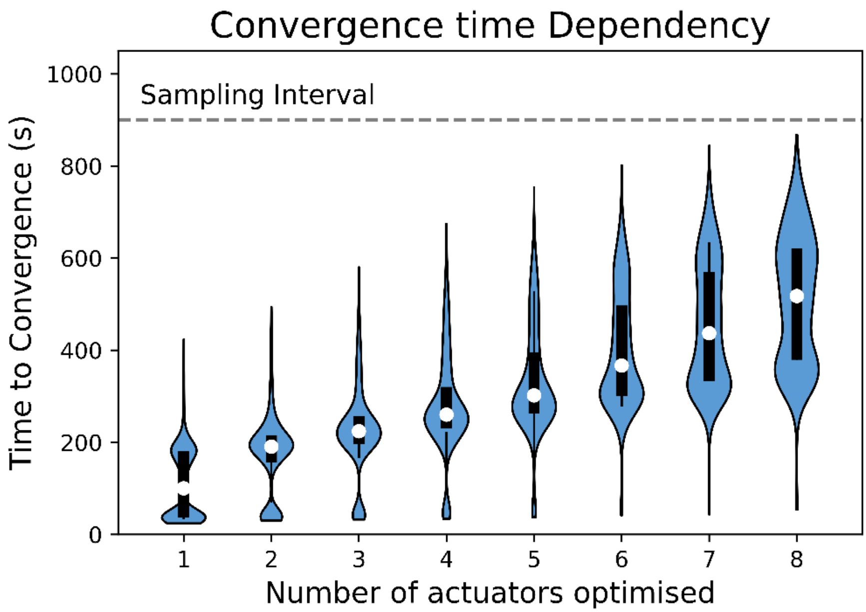


Figure B.1: Distribution of the times to convergence of the genetic algorithm in the HAPPy procedure, with a changing number of actuators

B.3. DETAILED BREAKDOWN OF THE PERFORMANCE - EVENT 1

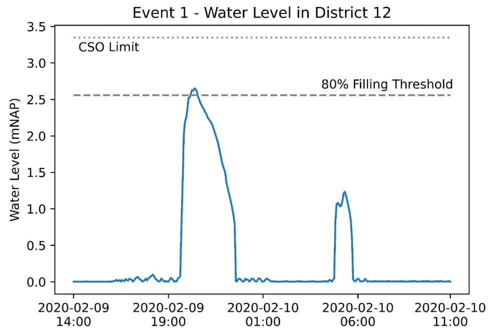
Limited to one actuator, the HAPPy procedure selected, intermittently, the regular and CSO pumps of district 12 for optimisation during the peak causing the CSO. The reduction in CSO volume observed is due to the re-activation of the regular pump (which is switched off following the heuristic rules), resulting in the earlier de-activation of the pumped CSO (see Figure B.3). When the CSO pump was selected as the most impactful actuator (for one sampling interval during the optimisation procedure), the algorithm assigned a value of 0 (equivalent to switching the pump off) to reduce the CSO emissions from the area. However, as the regular pump was, during this time step, following the pre-set rules, both pumps remained switched off, therefore only creating an interval in the CSO emission, as the volume of wastewater stored District 12 was not reduced.

Consequently, a minor increase in the CSO volume at District 4 was observed, as the filling degree threshold exceedance lasted an additional interval.

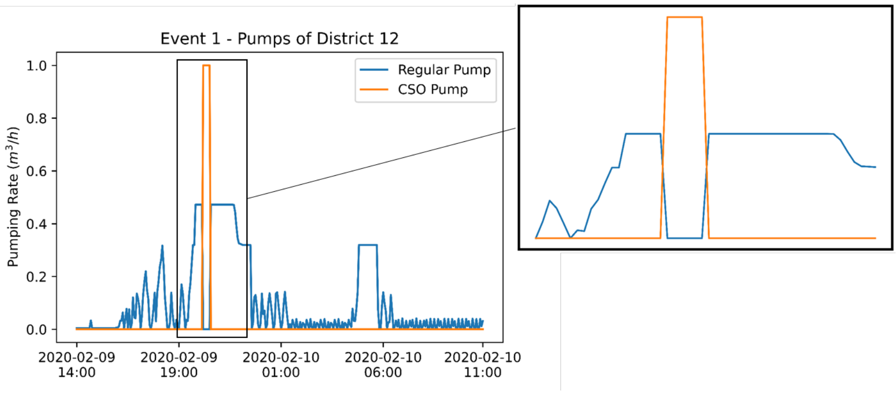
These dynamics were partially overcome when two actuators were selected, allowing the simultaneous closing of the pumped CSO and switching on of the regular pump at District 12, provided the correct actuators were selected. During the event, the regular pump was selected during all the relevant time steps, and the optimisation procedure found the complete opening to be the most optimum. The pumped CSO was selected in most of the time steps and was switched off following the optimisation procedure. For five actuators included (see Figure B.4), the entire event was negated.

Whereas event 1 resulted in a change in the binary *on-off* settings of the selected actuators, in this run partial (de-)activation (e.g. using 20% of the available capacity when either 100% or 0% would have been used through the heuristics procedure) of relevant pumping capacities were commonplace. This partial (de-) activation lead to a local decrease in both pumped and non-pumped CSO volumes as both static and dynamic capacities in the system were better utilised.

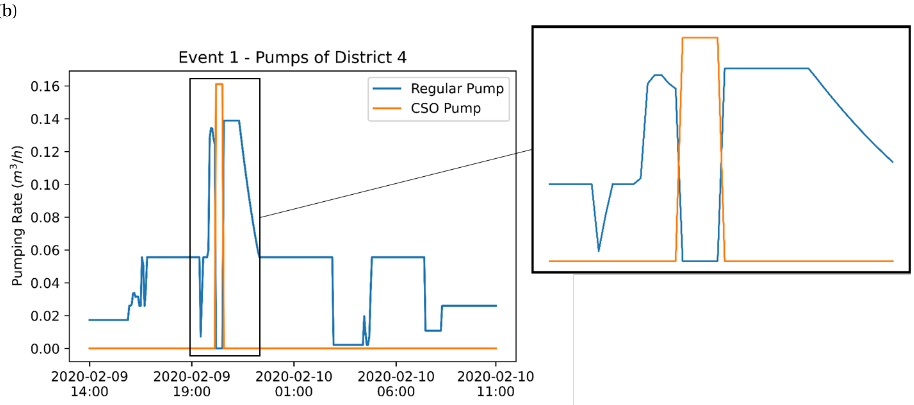
B



(a)

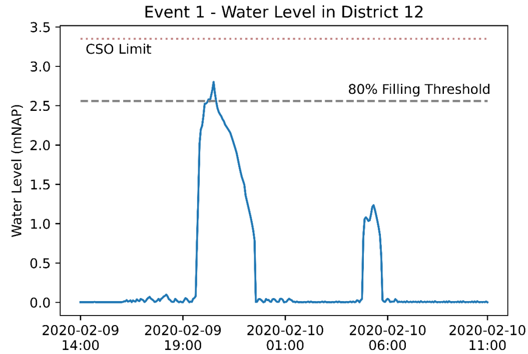


(b)

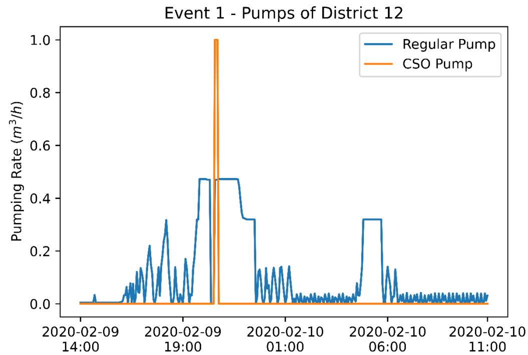


(c)

Figure B.2: The dynamics leading to the preventable CSO volume pumped during the heuristic control run: (a) Water level, including the 80% threshold, during the first event at sub-catchment 12. The 80% threshold was exceeded, leading to the activation of both PCSO12 and PCSO4. (b) the pumps associated with District 12, showing the on-off dynamics of both pumps pumping from District 12



(a)



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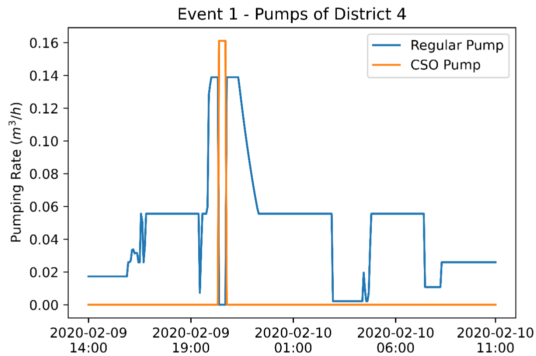
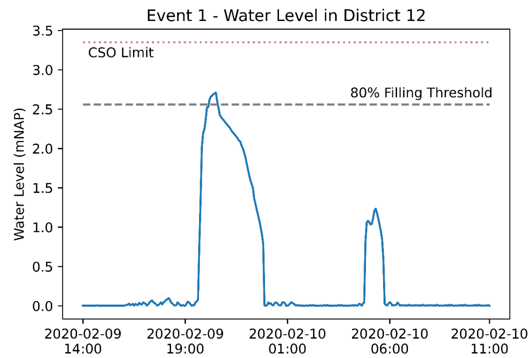
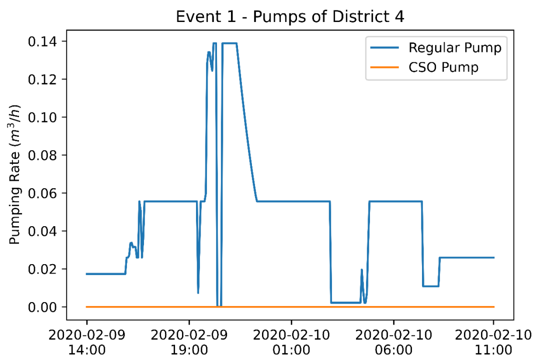


(c)

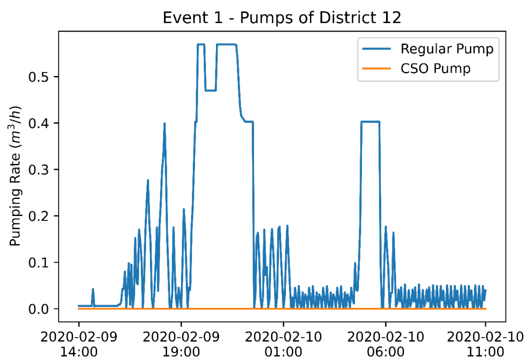
Figure B.3: Overview of the same data as Figure B.2, but including one actuator in the HAPPy procedure



(a)



(b)



(c)

Figure B.4: Overview of performance with 5 actuators included in the HAPPy procedure, leading to the effective full negation of the pumped CSO volume

C
Control Rules and GA Hyperparamters for Long Term Changes Analyses

C.1. GA Parameters for Optimisation

Below the GA hyperparameters used for the optimisation of the WWTP Eindhoven catchment followed by the hyper parameters used in the WWTP Hoogvliet case are shown. Notice that the population size of the Hoogvliet catchment is larger, which is permitted due to the relative speed and shorter sampling interval compared to the Eindhoven catchment.

Table C.1: Hyperparameters used for the optimisation of Eindhoven Catchment

Hyperparameter	**Value**
Number of Iterations	75
Population Size	25
Mutation Probability	0.1
Elite Ratio	0.05
Crossover probability	0.5
Parents Portion	0.2
Max Iteration without Improvement	15

Table C.2: Hyperparameters used for the optimisation of Hoogvliet Catchment

Hyperparameter	**Value**
Number of Iterations	75
Population Size	35
Mutation Probability	0.1
Elite Ratio	0.05
Crossover probability	0.5
Parents Portion	0.2
Max Iteration without Improvement	15

C.2. KEY HOOGVLIET DETAILS

The following set of details contains the connected area and storage volume per district in the Hoogvliet catchment. Additionally, pumping capacities are given. Thereafter, the main control rules are detailed.

Table C.3: Subcatchment Details for the WWTP Hoogvliet Catchment

Catchment ID	**Size (ha)**	**Volume (mm)**
J_1613	9.82	10.74
J_21	98.99	10.94
J_22	77.49	7.31
J_27	25.1	9.80
J_9013	75	14.15

Table C.4: Pumping Details for the WWTP Hoogvliet Catchment

Pump ID	**From Node**	**To Node**	**Max flow** ($m^3 s^{-1}$)
J_21 PS	J_21	WWTP	0.556
J_22 PS	J_22	WWTP	0.195
J_22 PCSO	J_22	Outfall	0.556
J_27 PS	J_27	WWTP	0.083
J_27 PCSO	J_27	Outfall	0.161
J_1613 PS	J_1613	J_22	0.018
J_9013 PS	J_9013	J_21	0.278

The following set of rules was optimised for the catchment of Hoogvliet as part of the CAS2.0 project, financed by the City of Rotterdam. The rest of the pumps are not explicitly considered in the CAS2.0 project and work with a simple local on and off threshold within the pumping station.

Table C.5: Overview of the heuristic procedure optimised for the WWTP Hoogvliet catchment

Actuator ID	**Catchment ID**	**Rule Details**
P 21 → WWTP	District 21	If the total discharge to WWTP > 3,300 $m^3 h^{-1}$, then reduce to 1,000 $m^3 h^{-1}$
P 22 → WWTP	District 22	If filling degree > 80%, reduce flow to 380 $m^3 h^{-1}$
PCSO 22	District 22	If filling degree > 80%, then ON
P 27 → WWTP	District 27	If filling degree > 80%, reduce flow to 0 $m^3 h^{-1}$
PCSO 27	District 27	If filling degree > 80%, then ON

D

Details on heuristic control of the Eindhoven case study

D.1. Detailed nowcast informed RTC procedures

Six nowcast-informed RTC (niRTC) procedures were developed as part of the methodology presented in Chapter 7. Below, these are explained in further detail.

Nowcast-informed RTC procedure #1

The first niRTC adds a bifurcation to the existing rules. In the existing rules, CSO pumps are switched on at a 80% filling degree (FD) in order to prevent local CSOs to spill. The bifurcation proposed here is to only use the CSO pumps when the FD > 80% and there is rainfall still predicted. If there is no rainfall predicted, there is no additional runoff expected to be generated, meaning that the CSO pumps can be switched off to save on both energy (not considered as an objective here, but a side benefit) and reduce the total CSO volume. A graphical representation of this is shown in Figure D.1

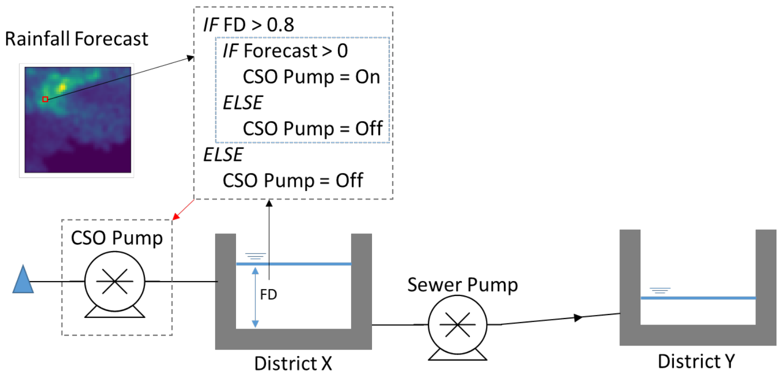


Figure D.1: Graphical representation of the first ni-RTC procedure

Nowcast-informed RTC procedure #2

In some parts of the catchment, it is preferable to switch off the sewer pump from one district to another when the downstream district has a filling degree higher than 0.8. This is done when the downstream district discharges into more sensitive urban canals compared to the upstream ones. Akin to the previous one, this switching off of the sewer pump is made conditional on the prediction of the end of the event. If no more rainfall is predicted, than the system switches back to a DWF state, in which all CSO pumps are switched off, and the sewer pumps are no longer switched off to protect the downstream catchments. This is show in Figure D.2.

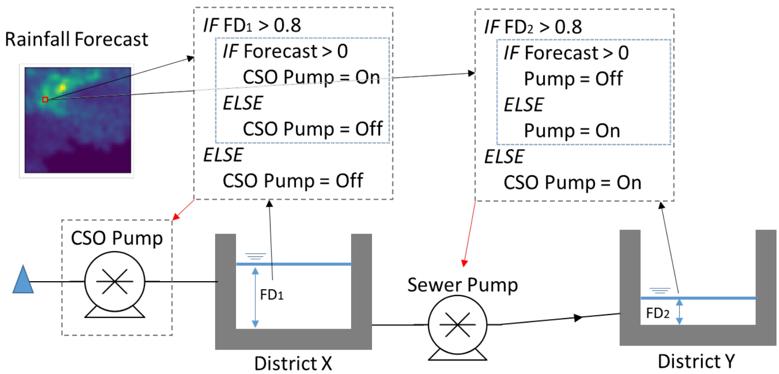


Figure D.2: Graphical representation of the second ni-RTC procedure

Nowcast-informed RTC procedure #3

The third niRTC procedure falls under the 'model-informed niRTC procedure' category. Effectively, the rainfall forecast is propagated through the simplified model, using the current observations of the system as initial-conditions. The maximum filling degree over the two hour horizon (using the baseline RB-RTC procedure in the internal MPC-model) for each of the districts is recorded. If this value is above 0.9, then the original on/off rules (i.e. CSO pumps on, and some sewer pumps off but with the threshold being higher) are implemented. This is done throughout the entire event and uses the entire forecast horizon. This is show in Figure D.3.

Nowcast-informed RTC procedure #4

The fourth niRTC procedure falls under the 'model-based niRTC procedure' category. Effectively, the rainfall forecast is propagated through the simplified model, using the current observations of the system as initial-conditions. The maximum filling degree over the two hour horizon (using the baseline RB-RTC procedure in the internal MPC-model) for each of the districts is recorded. If this value is above 0.8, then the original on/off rules (i.e. CSO pumps on, and some sewer pumps off) are implemented. This is done throughout the entire event and uses the entire forecast horizon. This is show in Figure D.4.

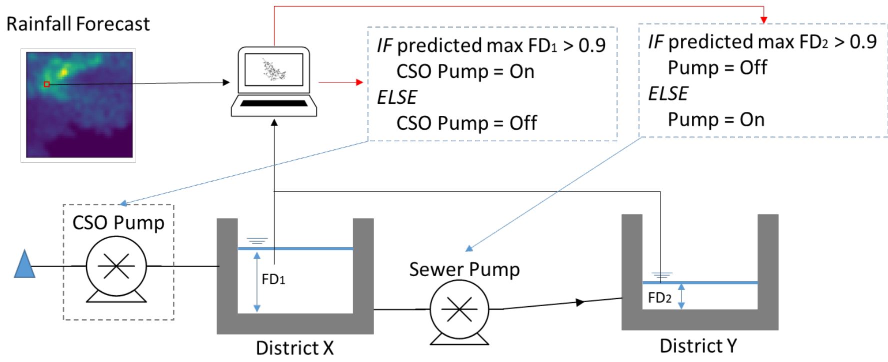


Figure D.3: Graphical representation of the third ni-RTC procedure

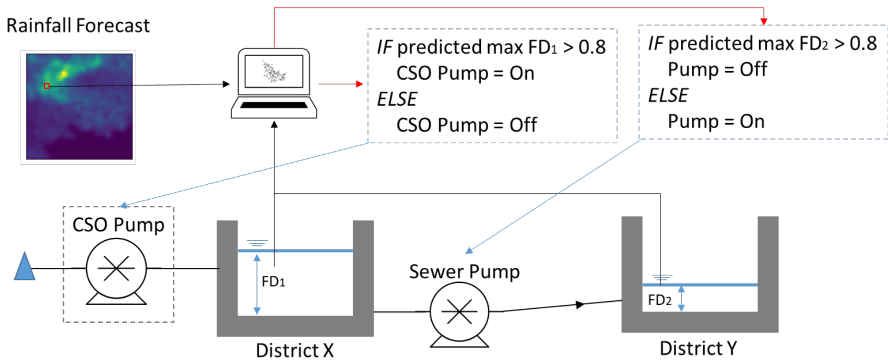


Figure D.4: Graphical representation of the fourth ni-RTC procedure

Nowcast-informed RTC procedure #5

The fifth niRTC procedure has a build in mechanism which tracks the forecast for an hour. If in that hour, the filling degree exceed 0.9 for at least 6 of those, the pumped CSOs are switched on and the relevant sewer pumps are switched off. The current measurement is weighted 6x as high as the rest, such that, if the current measurements indicate a filling degree of > 0.9, the system switches to the WWF states as indicated before. This is show in Figure D.5.

Nowcast-informed RTC procedure #6

The last niRTC procedure has a build in mechanism which tracks the forecast for an hour. If in that hour, the filling degree of the either the district itself, upstream district or downstream district exceed 0.8, for at least 6 of those, the pumped CSOs are switched on and the relevant sewer pumps are switched off. The current measurement is weighted 6x as high as the rest, such that, if the current measurements indicate a filling degree of > 0.8, the system switches to the WWF states as indicated before. This spatial compensatory

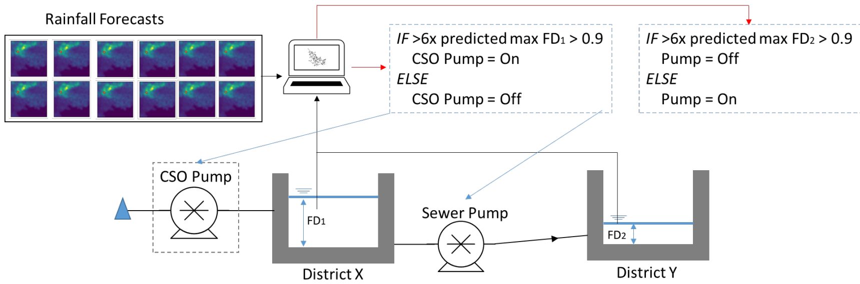


Figure D.5: Graphical representation of the fifth ni-RTC procedure

mechanism was designed to have a more conservative approach to the niRTC procedure, but relying on multiple forecasts locations and following the worst case scenario of those. This is show in Figure D.6.

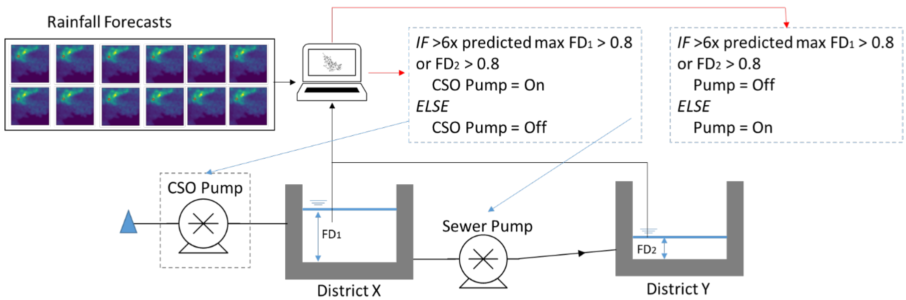


Figure D.6: Graphical representation of the sixth ni-RTC procedure

D.2. RTC POTENTIAL BREAKDOWN

Various dynamics in the system were identified which gave the rise to the potential for the improvement of the heuristic procedure. Here, these dynamics are described further and examples (from the events highlighted in Figure 7.4) are provided.

The first point was the potential to deactivate the CSO pumps when the rainfall event was over (or effectively over, by being below a certain threshold). The key role of the CSO pumps is to protect the inner city canals by discharging to the Nieuwe Maas (a large river). Although the ecological and public health hazards associated with these discharges is relatively slim, the minimisation of the pumped CSO volume is still a priority. Switching the pumps off at the end of the rainfall event, even if the FD is above 0.8, can reduce this with minimum risk.

As can be seen in Figure D.7, the CSO pump is active whilst the depth of the virtual reservoir is stable. This activation coincides with the deactivation of the sewer pump to protect the downstream reservoirs. From a mass-balance, the activation of the CSO pump could have been avoided, as the total volume discharged did not exceed the static capacity of the system.

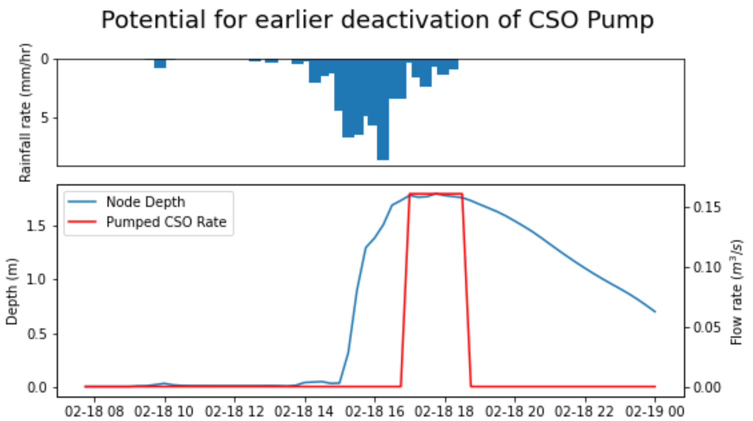


Figure D.7: Activation dependent on the filling degree. The duration of the pumped CSO event here continues even when there is very little rainfall (below $1mmhr^{-1}$), which can be captured by both the static capacity and the pumping capacity of the district.

It could be argued that using a nowcast prediction to activate the CSO pump only if this threshold (including a safety margin if preferred) is exceeded could be an additional measure to improve the system. This would lead to an earlier activation of the pumped CSO events, in the case of larger rainfall events, potentially reducing the spill to the internal city canals by activating the pumps earlier. An example of this can be shown on Figure S9, where the pumped CSO is activated, though the relative large rainfall peak that caused the uncontrolled CSO could have been predicted in order to activate the pumped CSO earlier, and thereby avoiding the uncontrolled CSO from occurring.

The procedural logic here hinges on switching earlier to switching to the FD > 0.8 procedures for the pumped CSOs. This procedural logic can be extended to all the rules in the niRTC, i.e. also affecting the sewer pumps and the distribution of the pumping capacity accordingly. This could further improve the system, with examples . The rules could further be improved by also considering forecasted heterogeneity in the rainfall. If there is significantly less rainfall falling downstream, the protection of those areas takes less priority, meaning a more optimal redistribution of the pumping capacities could be reached (by allowing the pumps to pump more downstream where the original RB-RTC would have shut it down due to the risk of CSOs occurring in the internal urban canals.

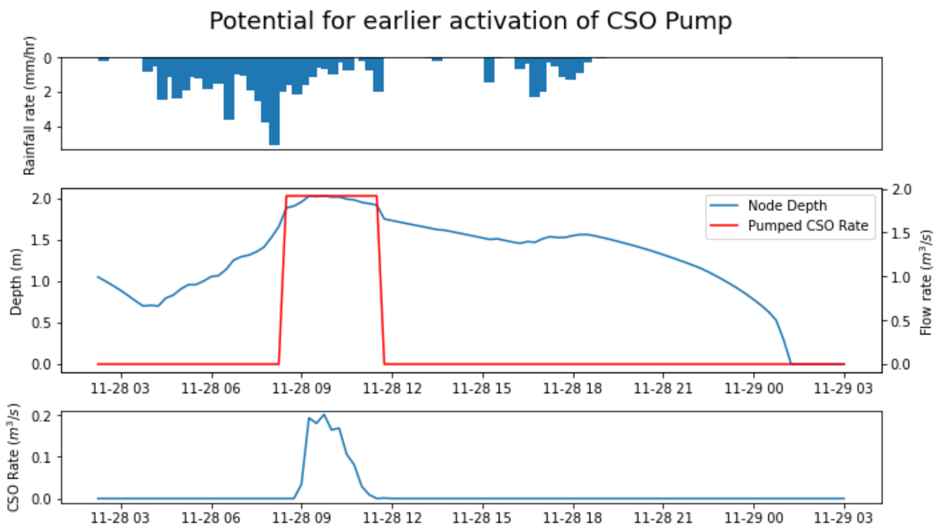


Figure D.8: Example of how switching earlier could have prevented an uncontrolled CSO from happening

Acknowledgements

For as long as I can remember I wanted to do research, and I want to start by thanking all of those along the way who have helped me, created opportunities for me, and supported and motivated me.

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Although my PhD time was rather rudely interrupted by a global pandemic, the many coffee breaks I've had with my "roommates" were more helpful than any Zoom meeting. Antonio (also for explaining all things PhD and modelling during my first couple of months), Bram (sharing great times abroad, shovelling sand and sharing a desk for the first year), Eva (for all the chats and good times), Kostas (for always keeping me guessing), Matthijs (for all your vrolijkheid), you made me feel welcome in 4.64 from day 1. With Juan, João, Aashna, Ariana, Alex and, in theory, Roberto we continued the coffee break tradition post-pandemic and I thank you for all the interesting conversations over the last few years. And thank you to all the other colleagues at TU Delft with whom I have shared many a lunch and chat about research and "PhDing". Diana, Javier, Simon, Sofia, Sara, Carina, Roos, Emiel, Gladys, Iosif, Anurag, Tugba, Yana, Katja and Omar, just to name a few (though I mean all those PhDs I've crossed paths with). Riccardo, Miriam, Mariska and all those other staff members at the TU that I have worked or interacted with, all those conversations have been very inspiring and I hope to continue them the coming years. Alba, you played a big part in supporting me throughout my PhD time, so thank you so much for that.

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List of Publications

Peer Reviewed Journal Publications

Farina, A., Di Nardo, A., Gargano, R., **van der Werf, J.A.** and Greco, R. (*Under Review*). A simplified approach for the hydrological simulation of Urban Drainage Systems with SWMM. *Journal of Hydrology*

van der Werf, J.A., Kapelan, Z. and Langeveld, J. (*Under Review*). HAPPy to Control: A Heuristic And Predictive Policy to Control Large Urban Drainage Systems. *Water Resources Research*

van der Werf, J.A., Kapelan, Z. and Langeveld, J. (*Under Review*). The Impact of Blue-Green Infrastructure and Urban Area Densification on the Performance of Real-Time Control of Sewer Networks. *Water Resources Research*

van der Werf, J.A., Kapelan, Z. and Langeveld, J.G. (2023). Predictive Heuristic Control: Inferring Risks from Heterogeneous Nowcast Accuracy. *Water, Science & Technology*, **87**(4): 1009-1028.

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International Conference Publications

van der Werf, J.A., Kapelan, Z. and Langeveld, J. (2022). HAPPy to Control: A Heuristic And Predictive Policy for RTC. In Proceedings of the 10th International Conference on Sewer Processes and Networks. Graz, Austria.

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Book Chapters

Schellart, A., Blumensaat, F., Clemens-Meyer, F., **van der Werf, J.**, Mohtar, W.H.M.W., Ramly, S., Muhammad, N., Bonneau, J., Fletcher, T., Costelloe, J.F., James, R., Burns, M., Poelsma, P., Ochoa-Rodriguez, S., Bourne, D., Hancock, Z., Wallwork, G., Hale, J., Nikolova-Peters, N., Kroll, S., van Assel, J. McCarthy, D., Shi, B., Bloem, S. and Ebi, C. (2021). Data collection in urban drainage and stormwater management systems - case studies. In Bertrand-Krajewski, J., Clemens, F. and Lepot, M. *Metrology in Urban Drainage and Stormwater Management, Plug and Pray.* London, UK. IWA Publishing

About the Author

Job Augustijn van der Werf was born on 8th of October 1995 in Haarlem, the Netherlands. There he finished his bilingual Gymnasium at *het Mendelcollege*. He then moved to Scotland, to study Civil and Environmental Engineering at the University of Strathclyde, Glasgow. An interest in water quality-related issues was sparked during surfing trips to Machrihanish and Pease Bay and whilst wakeboarding in the Glasgow Canals. Through an exchange programme to Universidad Politécnica de Valencia, Spain and writing a thesis on *microbial sequestration of heavy metals in sustainable urban drainage systems* he ended up further interested in computational tools for water quality improvements, particularly around things that cannot be easily seen. This led to a PhD project at the Delft University of Technology on factors influencing real-time control efficacy. Most of the work done during that PhD is presented in this work. During his time as a PhD, he also contributed to the design of the new MSc Environmental Engineering at the TU Delft as a full-time position for half a year. From the first of April 2023, he started as an Assistant Professor Urban Water Systems at the Delft University of Technology, continuing his research in the field of urban drainage.

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