Modelling the Effects of In-Sewer Buffering of Dry Weather Flow on Surface Water Quality

Quantifying the effects of more constant wastewater treatment plant influent on effluent quality

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by

J. R. Steiger

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Cover: Drone image of wastewater treatment plant installation of Eindhoven obtained from Algemeen Nederlands Persbureau

TU Delft

Preface

I am writing this thesis to conclude my Master's in Environmental Engineering degree at the Delft University of Technology. This particular topic appealed to me because it combines my interest in programming, the urban environment, and hydraulic engineering. It deepened my knowledge of control strategies and integral system behaviour in the urban water cycle.

The research presented in this thesis is intended for readers interested in urban drainage systems, real-time control architecture, and the entire urban water cycle. To fully grasp the work presented in this work, general knowledge of urban drainage systems and control schemes is recommended. Readers interested in the relevance, other related work, or the objective of this thesis should read Chapter 1. While readers interested in the applied methodology should skip to Chapter 3. Others who prefer to move directly to the results are best advised to move on to one of 3 chapters: the Abstract, Chapter 4, or 6. Lastly, those who would like to continue with the ideas presented here are recommended to read chapter 5.

Finally, I would like to express my gratitude to my daily supervisor, Dr. J. A. van der Werf, for his continuous enthusiasm, clever solutions, and for always being available for questions. Moreover, I would like to thank the remaining assessment team, consisting of J. G. Langeveld, M. Ronteltap, and A. G. Droste, for their valuable feedback and time. I am also grateful to all other sanitary engineering employees of TU Delft who made me feel so welcome. Furthermore, I am immensely grateful to L. Benedetti for his support throughout this thesis with WEST. I would also like to thank my parents for their continuous support of my studies. And finally, my girlfriend, thank you for your day-to-day encouragement, saving my sanity at times, and keeping me level-headed.

J. R. Steiger
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Abstract

With increasing focus on global clean water goals and stricter surface water quality legislation within the European Union, new strategies are needed to improve the performance of urban drainage systems. Wastewater treatment plants play a key role in nutrient removal for better surface water quality. However, the highly variable inflow from combined sewer systems–driven by both diurnal wastewater patterns and rainfall–can hinder optimal wastewater treatment plant operation, often resulting, amongst others, in elevated nitrogen and phosphorus levels in the wastewater treatment plant's effluent.

This study proposes a real-time control strategy that stabilises dry weather flow by actively using in-sewer storage, thereby minimising daily inflow fluctuations to the wastewater treatment plant. The method was applied to the Eindhoven wastewater treatment plant catchment, focusing on its two largest contributing catchments, Eindhoven and Riool Zuid. A simplified Storm Water Management Model model, based on an existing integral system model, was combined with a PySWMM-based control script and an empirical water quality model to estimate pollutant concentrations. Control decisions were based on current and forecasted rainfall, using both perfect (historic) and ensemble-based forecast data, determining four possible operational states: dry, transition, wet, and lingering wet weather.

This research demonstrates that dry weather flow control can improve daily wastewater treatment plant and surface water effluent peak concentrations without additional negative effects on the urban drainage system itself–for improvement in averages of effluent or surface water, additional treatment plant operational adjustments are required. The study also showcased the potential of real forecasts, with inherent uncertainty, in quantitative real-time control decision making. Lastly, the study underlines the potential of integrated, forecast-based control strategies to better align urban drainage and treatment plant operation, encouraging further development of a feedback-based optimisation framework.

Contents

Nomenclature

Abbreviations

Abbreviation	Definition
SDG	Sustainable Development Goal
UDS	Urban Drainage System
WWTP	Wastewater Treatment Plant
CSO	Combined Sewer Overflow
BOD	Biochemical Oxygen Demand
NH_4	Ammonium
CO_2	Carbon Dioxide
CH_4	Methane
NO_2	Nitrous Oxide
TSS	Total Suspended Solids
COD	Chemical Oxygen Demand
EU	European Union
WFD	Water Framework Directive
UWWTD	Urban Wastewater Treatment Directive
p.e.	Population Equivalent
TN	Total Nitrogen
TP	Total Phosphorus
EQS	Environmental Quality Standards
NH_4-N	Ammoniacal Nitrogen
RTC	Real Time Control
DWF	Dry Weather Flow
SWMM	Storm Water Management Model
PySWMM	Python Interface to Storm Water Management Model

Table 1: Abbreviations used in this report, in order of occurrence

1 Introduction

Clean water and sanitation are one of the 17 Sustainable Development Goals (SDGs) established by the United Nations. Key targets include ensuring safe and affordable water for all, providing adequate sanitation, improving surface and groundwater quality by reducing polluting and hazardous discharges, and halving the proportion of untreated wastewater entering the environment (United Nations, 2015). In many cases, people without access to safe drinking water are forced to consume water from unsanitised sources, heightening their risk of illness and infectious diseases such as cholera, diarrhoea, hepatitis A, and polio (Ritchie et al., 2019; Khalifa and Bidaisee, 2018). A major contributor to a lack of safe drinking water is surface and groundwater pollution, often resulting from human activities such as the discharge of (un)treated wastewater and agricultural runoff. These sources of contamination are the main source of water supply pollution and further negatively affect local (wildlife) populations, ecosystems, and ecosystem services (Trebuch et al., 2024; Wolfram et al., 2021).

To prevent water pollution from urban sources, modern urban drainage systems (UDS) are designed to collect both stormwater and wastewater, using either combined or separated sewer systems. In a combined system, both stormwater and wastewater are conveyed through a single pipe to a wastewater treatment plant (WWTP), where the mixture of both is treated to meet water quality standards. Alternatively, a separated system transports only wastewater to the WWTP, while stormwater is discharged directly into receiving surface waters, such as rivers or canals, using a different pipe for each medium. Each system has advantages and disadvantages: Combined systems are generally cheaper and easier to construct and maintain, but require WWTPs capable of handling increased flows during storm events. In cases of severe storm events, combined sewer overflows (CSOs) can be activated to prevent surface flooding, however, at the cost of surface water pollution by discharging untreated waste and stormwater to the receiving surface waters. Separated sewers, on the other hand, offer lower CSO risk and more consistent inflow to the WWTPs, improving treatment efficiency. However, they are more expensive and susceptible to illicit connections, which are difficult to locate and can lead to surface water pollution. Moreover, the directly discharged stormwater, polluted during urban surface runoff, further contributes to surface water pollution. Furthermore, as sanitation and wastewater management have changed significantly over time, current urban drainage systems combine older and newer sections of infrastructure, which requires a historical understanding. Early civilisations such as Mesopotamia and the Indus Valley developed basic drainage systems, while ancient Rome introduced more advanced centralised sewers. After the fall of Rome, the Middle Ages saw a regression, with cities relying on cesspits and inadequate drainage. Renewed progress came in the 19th century, prompted by urban sanitation crises like London's "Great Stink" and Paris's redevelopment under Haussmann. Centralised sewers were constructed, often under the mistaken belief that dilution alone was sufficient. The 20th century marked the start of modern treatment, with innovations like biochemical oxygen demand (BOD) testing and activated sludge processes. Today, advanced technologies include nutrient removal, membrane bioreactors, and disinfection methods such as chlorination, ozonation, and ultraviolet treatment, often paired with sustainable strategies for solids reuse (Lofrano and Brown, 2010).

Within the urban drainage system, various sources of pollution exist. The rapid discharges of CSOs elevate concentrations of pollutants, including plastics, sanitary products, heat (which can alter thermal regimes), suspended solids (from resuspension during high flows), and charged ions like chloride in the receiving waters (Perry et al., 2024; Madoux-Humery et al., 2016). While WWTPs are designed to reduce pollutant levels to within regulatory standards, their effluent can still negatively impact surface waters, particularly when influent loads are high or when receiving waters are sensitive due to low flow levels. WWTPs also contribute to greenhouse gas emissions, including carbon dioxide (CO_2), methane (CH_4), and nitrous oxide (N_2O) (Kampschreur et al., 2009), with NO_2 from WWTPs accounting for approximately 3.4% of global emissions (Edenhofer, 2015; Kampschreur et al., 2009). In addition, urban runoff introduces significant loads of total suspended solids (TSS), chemical oxygen demand (COD) and heavy metals into both WWTPs and surface waters (Gnecco et al., 2005). Combined, these factors degrade the microbiological water quality by lowering oxygen levels, increasing faecal contamination, promoting eutrophication and causing hydraulic stress in receiving waters (Langeveld et al., 2013; Passerat et al., 2011). Additionally, flow variability–caused by diurnal wastewater patterns and weather-driven stormwater surges–can affect WWTP performance (Grady Jr et al., 2011), often resulting in elevated ammonium (NH_4) concentrations in effluent. This may lead to oxygen depletion due to increased bacterial activity, nitrogen toxicity harming aquatic life, or algae bloom (Langeveld et al., 2013).

Recognising these challenges, the European Union (EU) created a comprehensive legislative framework. The cornerstone of this framework is the Water Framework Directive (WFD) (Directive 2000/60/EC). The framework mandates states to achieve 'good ecological and chemical status' for all surface waters and 'good quantitative and chemical status' for groundwater, originally by 2015 with extensions to 2027 (The European Parliament and the Council of the European Union, 2000). To control point-source pollution, the Urban Wastewater Treatment Directive (UWWTD) (91/271/EEC) sets effluent standards for municipal WWTP effluent (The Council of the European Communities, 1991). To address emerging challenges, the European Commission introduced a proposal to revise the UWWTD in October 2022 (COM(2022) 541 final), with agreement reached in early 2025 (European Parliament and Council of the European Union, 2024). This revision places greater emphasis on water-energy-nutrient circularity, aiming for energy neutrality in the sector, and enhances urban resilience to heavy rainfall. To reach a better surface water status, the revised standards place greater emphasis on nutrient removal by making the regulations significantly stricter. For larger agglomerations (>100 000 population equivalent (p.e.)), the limits in WWTP effluent for Total Nitrogen (TN) are tightened to 8 mg/L and Total Phosphorus (TP) to 0.5 mg/L. These limits are measured, in agglomerations of 150 000 p.e. or above, twice per week using 24-hour composite samples collected continuously or at regular intervals. The annual mean of these samples must comply with the prescribed limits. Furthermore, it introduces mandatory 4th step treatment for the removal of a broad spectrum of micro-pollutants, such as pharmaceuticals, funded through an 'Extended Producer Responsibility' scheme (European Commission, 2022). These effluent standards are designed to help achieve the WFD's goals for receiving water bodies. Additionally, the International Commission for the Protection of the Rhine (ICPR) has established surface water quality norms for Rhine-relevant substances. Based on a water temperature of 15 $^\circ C$, and a pH of 7, an annual average limit of 0.479 mg/L and a peak concentration limit of 0.763 mg/L have been defined for total nitrogen levels (Internationale Commissie ter Bescherming van de Rijn, 2019).

To reach the set regulations, various pathways can lead to improved WWTP effluent quality: expanding treatment capacity, implementing more advanced treatment technologies, or optimising existing operational conditions. Capacity expansion typically involves the construction of additional or larger treatment units, an effective but capital-intensive solution. Alternatively, new treatment technologies, though often slower to develop and implement, can target emerging contaminants; for example, pharmaceuticals are increasingly addressed through a fifth treatment stage employing advanced oxidation processes such as ultraviolet irradiation or ozonation (Voigt et al., 2020). Lastly, optimising existing operational conditions by using "smart" strategies, particularly through real-time control (RTC), can improve the UDS's water quality-related performance. RTC applies dynamic control of pumps, valves, and gates based on real-time flow or water level measurements throughout the sewer network (Webber et al., 2022). It offers a relatively low-cost solution by using existing infrastructure and control elements, requiring only measurement data, sensors, and control equipment. When implemented effectively, RTC can significantly reduce CSO volumes and improve WWTP effluent quality (Beeneken et al., 2013; Dirckx et al., 2011; Seggelke et al., 2005).

The RTC method is often used to enhance urban resilience to heavy rainfall, with the primary objective of improving the receiving surface water quality. This goal is achieved by optimising the available storage volume in sewer networks to reduce the frequency and magnitude of polluting CSO events, and by regulating inflow to the WWTP to prevent hydraulic overloading and thereby improving its treatment performance during wet-weather conditions (van der Werf et al., 2023; Kroll et al., 2016; Vezzaro and Grum, 2014). Three general objectives can be identified: volume-based control, which tries to minimise the total CSO volume, pollution-based control, which aims to minimise the total amount of pollutants entering receiving waters, and emission-based control, which aims to maximise the receiving water quality (Sun et al., 2020). Emission-based control most directly addresses the primary objective of improving surface water quality, but it is also the most complex to implement. This makes pollution-based control a suitable and practicable alternative. Volume-based control is cheaper and easier to implement, only requiring flow and depth sensors, while still making a considerable difference in CSO discharges. Overall, RTC allows for a more efficient use of the existing systems, allowing for extension of its lifespan, and thereby delaying expensive and large footprint expansion.

Research into the benefits and drawbacks of RTC in urban drainage systems mainly focuses on the effects during wet weather conditions. In its most generic form, research or models are created to reduce combined sewer overflow or to prevent/delay expensive storage expansion by optimising the flow regime during storm events as described in van der Werf et al. (2023), Meneses et al. (2018), Vezzaro and Grum (2014). Other research also considers the wastewater treatment plant effluent quality, or throughput capacity (Vanrolleghem et al., 2005). Other forms of RTC use precipitation forecasts, such as the DORA approach (Vezzaro and Grum, 2014), which combines information about present water volume in the system, forecasted runoff volume, and forecast uncertainty to reduce CSO volumes. Similarly, different nowcast-informed (using very short-term precipitation predictions) rule-based control procedures are analysed in van der Werf et al. (2023). This paper highlights the fact that nowcast-informed RTC can significantly reduce pollution load from urban drainage systems and that the uncertainty in the nowcast is heterogeneous, leading to potential poor(er) performance. Besides wet-weather operation improvements, RTC can be used to improve wastewater treatment operation by buffering wastewater influent–the temporary storage of waste and storm water during peak inflow periods, allowing its controlled release during off-peak times–at the treatment plant, leading to a more constant supply of wastewater to the treatment facility (van Daal-Rombouts, Benedetti, de Jonge, et al., 2017). This controlling of the dry weather flow (DWF) comes with several advantages; it extends the lifetime of current systems by providing better effluent quality with the same physical systems, and depending on the energy prices, a more cost-effective treatment planning can be employed (Langeveld and Voorthuizen, 2019; Dijk et al., 2013; Mulder et al., 2000). Both lifetime extension and energy efficiency are already sought-after objectives to reduce costs.

In Mulder et al. (2000), the optimisation of the Rotterdam treatment plants is discussed by employing different RTC strategies, including RTC of dry weather flow. It further mentioned that the effectiveness of the treatment is strongly dependent on the influent pattern, highlighting a potential for its improvement by flattening the wastewater inflow. This potential is supported by both Troutman et al. (2020) and Langeveld and Voorthuizen (2019), claiming that wastewater flattening can lead to better effluent quality levels to help pass effluent discharge legislation and higher treatment efficiency. Flattening of the wastewater treatment plant inflow has been researched in van Daal-Rombouts, Benedetti, de Jonge, et al. (2017), where buffer tanks are used to, amongst other factors, reduce peak loading of the activated sludge tanks. The primary goal of DWF buffering is to create a more stable and predictable pollutant load entering the WWTP by strategically using the storage capacity within the existing drainage network. Biologically, the WWTPs function more efficiently and produce cleaner effluent when the influent has a more constant flow and pollutant load. However, it has been shown that limitations exist when simply flattening the hydraulic flow. As Langeveld and Voorthuizen (2019) have shown, transport time within the drainage system causes a temporal shift between peak flow and peak pollutant concentration. This means that pollutant mass load (flow x concentration) can arrive at a time different from peak water flow. Managing this peak load would require more advanced RTC to steer based on the anticipated pollutant load, to flatten the WWTP influent. Even though this approach can improve effluent quality and potentially delay costly WWTP expansions, it is not without trade-offs. Storing wastewater for extended periods within the sewer system–to buffer–can increase the risk of sedimentation and anaerobic conditions, leading to issues with odour and corrosion, and higher maintenance costs for the sewer network itself (Langeveld and Voorthuizen, 2019). Additionally, it leads to a higher risk in case of significant storm events, which may lead to more harmful CSO events. Furthermore, the buffering in van Daal-Rombouts, Benedetti, de Jonge, et al. (2017) ultimately led to a significant improvement in maximum event concentration and load of NH_4 concentrations in the effluent during significant storm events while providing little to no benefit in medium to small events. For better optimisation of WWTP pollutant influent, models that predict influent concentration levels are proposed in both Vezzaro et al. (2020) and van Daal-Rombouts, Benedetti, de Jonge, et al. (2017). Both models predict the NH_4 levels, while the latter is also able to predict COD levels. Such models are helpful in RTC applications using either pollution-based or emission-based control.

While real-time control in urban drainage systems has been extensively studied, relatively little attention has been given to optimising wastewater treatment plant inflow during dry weather conditions (van der Werf et al., 2023; Meneses et al., 2018; Vezzaro and Grum, 2014). This represents a critical gap, as previous research has demonstrated that high variability in influent flow can reduce treatment efficiency, degrade effluent quality, and, as a result, lower surface water quality (Grady Jr et al., 2011). In contrast, stabilising the inflow-—particularly during dry weather-—has the potential to improve WWTP influent conditions, allowing for a better treatment process and cleaner effluent and surface water (Langeveld and Voorthuizen, 2019; Troutman et al., 2020). Although several tools are available, including RTC strategies, influent prediction models, and approaches to handle forecast uncertainty, these have not been systematically applied to regulate dry weather flow.

This thesis addresses that gap by investigating the following research question: To what extent can real-time control of dry weather flow improve the stability of influent to the Eindhoven WWTP, and what is the resulting impact on effluent quality and surface water quality? The study focuses on two major catchments connected to a single WWTP—Eindhoven and Riool Zuid, located in the south of the Netherlands. A heuristic, rule-based RTC approach is developed, using sewer hydraulic data and weather forecasts to actuate pumps. The effectiveness of this strategy is evaluated using an integrated modelling framework that combines sewer hydraulics, water quality modelling, WWTP, and river simulation. Water quality is assessed using total nitrogen and total phosphorus specifically.

The primary objective of this thesis is to evaluate how RTC of dry weather flow can enhance WWTP effluent and receiving surface water quality. To meet the research objective, the following sub-questions are defined:

1. How does the current system behave in various scenarios, and what are the current RTC-relevant characteristics of the system?
2. What is the improvement potential, in relation to WWTP effluent and surface water quality, of an RTC strategy with heuristic control rules using perfect precipitation forecasts by using historical data?
3. How does uncertainty in precipitation predictions through ensembles affect the performance of the RTC strategy and the WWTP?

Although reducing CSOs or mitigating urban flooding is not a primary objective, the implemented RTC rules are designed to avoid any increase in such events. The main objective is to improve the nitrogen and phosphorus concentration in the effluent of the treatment plant and in the most downstream section of connected surface water. Broader sustainability aspects, such as energy optimisation or effluent-based receiving water quality management, are considered outside the scope of this thesis. Similarly, more advanced controls, such as model predictive control to steer based on anticipated load, are considered outside the scope. Modelling is based on an existing UDS-WWTP setup, and no additional modifications are made to the WWTP's internal processes or control logic, meaning no further changes are made to the hydraulic residence time, sludge volume index, and so on. As such, results should be interpreted in the context of these limitations. Lastly, treatment plant emissions, such as N_2O, are unavailable due to model limitations.

2 Wastewater System Eindhoven

This chapter introduces the case study area used in this research: the urban wastewater system of Eindhoven and its contributing catchments. It outlines the key characteristics of the Eindhoven WWTP catchment, including its structure, flow dynamics, and relevance to water quality challenges in the Dommel River. The used data and models are described in detail, with emphasis on the available integrated model used for system calibration.

2.1. Urban Drainage Network

To best analyse the effects of the desired control logic, a WWTP catchment with a large area, that is thoroughly researched and has a well-modelled catchment and treatment plant, is required. For this reason, the connected system of the WWTP Eindhoven is chosen (Figure 2.1). This wastewater treatment plant is the 3rd largest WWTP in the Netherlands, with a total capacity of 750 000 people equivalent. The integrated model used during this project is based on the treatment plant as of 2012, consisting of three parallel treatment lines, each consisting of a primary settler, a biological tank, and four secondary settlers. The biological treatment follows a modified UCT configuration for COD, nitrogen, and phosphorus removal. The system includes a plug-flow anerobic tank, an anoxic carousel zone, and a facultative aerobic/anoxic outer ring with seasonal aeration control. Three circulation loops facilitate sludge and nitrate recycling between zones to optimise nutrient removal (Cierkens et al., 2012; Weijers et al., 2012). The receiving surface water of this WWTP effluent and most CSOs within the catchment is the river 'de Dommel', which is a relatively small river with a base discharge of just 2 to 4 m^3/s and particularly experiences problems with ammonia peaks due to WWTP effluent contributing up to 50% of total flow in the river during the summer period (Langeveld et al., 2013). For this particular type of river, a slow-flowing, sandy bottom river, the WFD has set a summer-average total nitrogen limit of 2.3 mg/L (The European Parliament and the Council of the European Union, 2000), a value superseded by the set limit of 0.473 mg/L on year average by the ICPR .

The contributing catchments to the WWTP include the Eindhoven catchment, accounting for 45% of the total inflow, Riool-Zuid also accounting for 45% of the total inflow, a southern sewer section connecting Veldhoven and various smaller villages, and Nuenen-Son providing the remaining 10%. In this research, only the larger 2 catchments are considered, leaving the remaining 10% from Nuenen & Son as an uncontrolled catchment, as it only has a limited contribution to the overall WWTP influent. The variability still present in this remaining 10%, should not have a large impact on the idealised constant WWTP inflow. Both catchments are a combined sewer network, where the Riool Zuid catchment is connected through a 30-odd-kilometre-long transport pipe, which is mainly free-flowing. In Aalst, a large pumping station is present, with a large upstream storage capacity. The Riool Zuid catchment is further divided into 3 sections: the Geldrop Catchment (including Heeze, Leende, and Sterksel), the Mierlo catchment, and everything upstream of the Aalst pumping station (Figure 2.1).

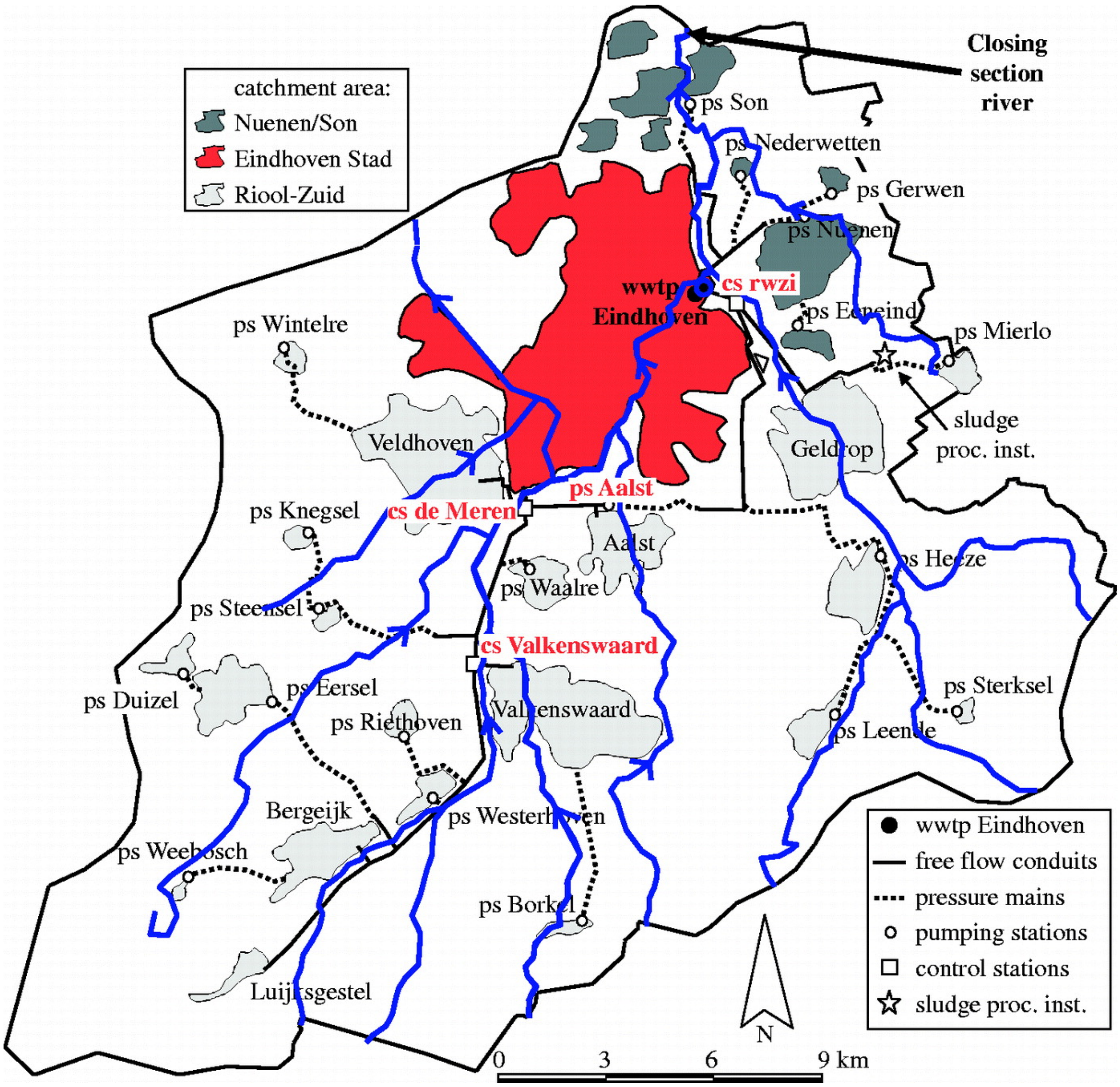


Figure 2.1: Schematic overview of the urban drainage system of Eindhoven, Riool Zuid, and Nuenen/Son taken from Langeveld et al. (2013)

To better understand how each of the 4 catchment relate to each other in terms of characteristics, such as average generated dry weather flow, in-sewer storage capacity, and total connected area, a table summarising the system characteristics is presented (Table 2.1). With the presented information, more informed decisions and analysis can be made when creating the RTC logic and reviewing the results. In the table, the storage capacity sum of Geldrop, Mierlo, and Aalst-upstream does not reflect the storage capacity of Riool Zuid. This is due to an introduced fully hydrodynamic section of the transport pipe, which links the 3 catchments together, having a storage capacity of 21 407 m^3. Each of the pumps leading out of Eindhoven and Riool Zuid are based on a pump curve dependent on upstream water depth, with a maximum flow rate of 3.888 and 4.7222 m^3/s, respectively. The catchment upstream of Aalst is connected to a pumping station operated by control logic dependent on upstream water depth, which enables either 1 or up to 4 pumps. The number of CSOs at Eindhoven says something about the number of outflow points to the Dommel river; in reality, only a single bucket exists in the Eindhoven catchment from which all these CSOs source. All other catchments have multiple locations from which CSOs can occur. Lastly, the implemented transport pipe, since it is free flowing, also has a CSO implemented; hence, the sum of CSOs from Geldrop, Mierlo, and Aalst upstream is just 14.

Table 2.1: System characteristics of the controlled catchments. Riool Zuid is the aggregated sum of Geldrop, Mierlo, Aalst-upstream, and a hydrodynamic section of the transport pipe

	Eindhoven	**Riool Zuid**	**Geldrop**	**Mierlo**	**Aalst-upstream**
Impervious Area [ha]	2045	2172.9	422.9	107.1	1642.9
Average DWF [m^3/s]	0.663	0.515	0.111	0.029	0.375
Average DWF [mm/hr]	0.1167	0.0853	0.0944	0.0975	0.0821
Piping Volume [m^3]	165000	252107	36400	8632	195668
Piping Volume [mm]	8.07	11.60	8.61	8.06	11.91
Pumping Capacity [m^3/s]	3.888	4.7222	0.8	0.191	0.56 - 2.1
Pumping Capacity [mm/h]	0.6844	0.7825	0.6811	0.6415	0.1227 - 0.4599
Number of CSOs [-]	15*	15	3	2	9

This WWTP and its contributing area have been thoroughly researched and modelled (van der Werf, 2023; van Daal-Rombouts, Benedetti, De Jonge, et al., 2017; Langeveld et al., 2013; Benedetti et al., 2012; Schilperoort, 2011). Schellart et al. (2021) provides a summary of all performed measurements in the region. Especially the Kallisto project (Weijers et al., 2012) is valuable for this research, as it provides a fully integrated sewer, wastewater treatment plant, and river model, using an empirical sewer model to generate WWTP influent based on Langeveld et al. (2017), providing the required valuable data and information for the creation of this thesis. The fully integrated model is created in the WWTP simulation software WEST by DHI (Vanhooren et al., 2003), combining all 3 urban drainage systems, the water quality model, the treatment plant, and the receiving waters. This existing model of the drainage systems and water quality model, in WEST, functions as calibration data for a newly created UDS model. Langeveld et al. (2013) also included a global sensitivity analysis, showing that the level of ammonium in receiving waters is sensitive to control actions, highlighting the potential for the proposed RTC. Benedetti et al. (2012) reiterates this by stating that NH_4 and PO_4 levels need to be reduced in order to comply with maximum summer average concentration levels. While basic pump curves are present, and some control logic for the pumping station within the used models, no coordinated RTC has been used as of yet within the integrated model. Additionally, this model has been studied in Moreno-Rodenas et al. (2019) to quantify the uncertainty in large integrated computer models that simulate river water quality. The key findings here were that while uncertainty is large, particularly due to pollutant sources–rather than river dynamics–the model is still useful in providing relevant information about the (relative) effectiveness of different management strategies.

2.2. Used Data

Precipitation (forecast) data is used to assess the performance of the RTC. Since the entire catchment of the Eindhoven treatment plant stretches a large connected area of over 40 km^2, assigning a single representative dataset for precipitation data and weather forecasts to this entire area would be an over-simplification of reality. To better fit the available dataset's grid-cell resolutions, the area is divided into 4 regions: Eindhoven, Geldrop and Mierlo, Riool Zuid-north, and Riool Zuid-south (Figure 2.2), where each region has its own rain gauge to which a dataset for precipitation and weather forecasts is assigned. These areas, represented by rectangular boxes, are used to filter and assign both precipitation and weather forecast datasets based on maximum and minimum latitude and longitude (Table 2.2).

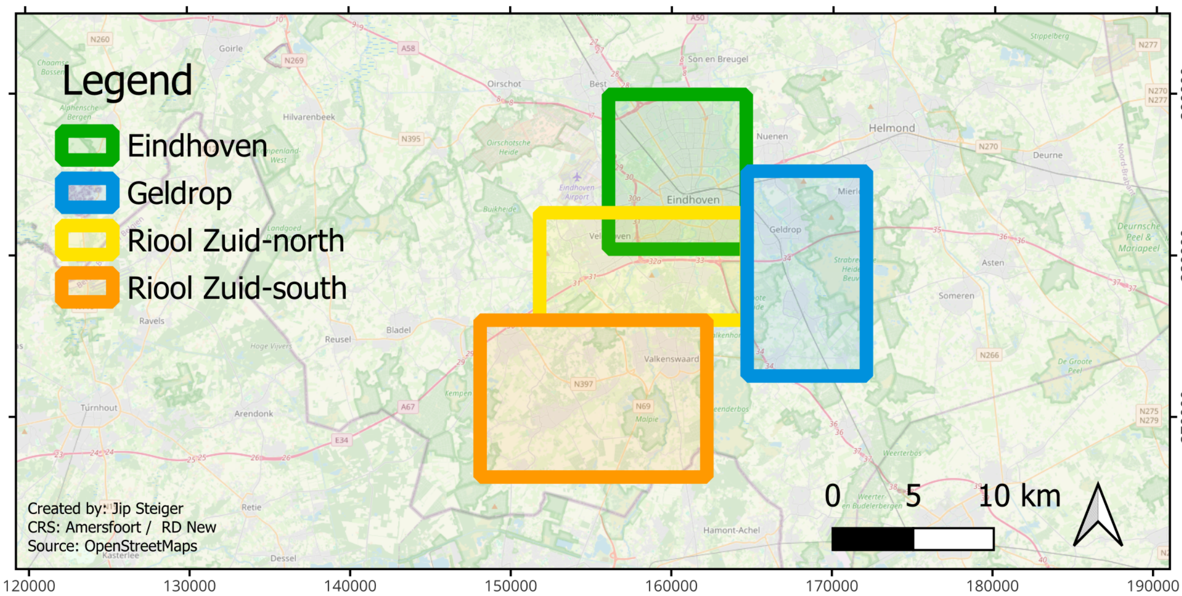


Figure 2.2: Rain gauge region borders represented as rectangular boxes, with the top right corner corresponding to the maximum latitude and longitude, and the bottom left corner to their minimum, with exact coordinates available in Table 2.2

Table 2.2: Rain gauge region border coordinates based on bounding boxes from Figure 2.2

Catchment region	Latitude max	Longitude max	Latitude min	Longitude min
Eindhoven	51.498	5.526	51.411	5.403
Geldrop	51.455	5.633	51.341	5.527
Riool Zuid-north	51.432	5.526	51.372	5.341
Riool Zuid-south	51.372	5.491	51.285	5.288

2.3. Used models

Some available and used models for the catchment have already been briefly mentioned. Which specific models are used, what they provide, and how they are used are detailed below. In this study, the following models are used;

- Integrated model of the Eindhoven WWTP catchment, treatment plant, and receiving water (Figure 2.3)
- Empirical Sewer Water Quality Model (included in the integrated model)
- Full hydrodynamic model of the Geldrop catchment & transport pipe (Figure 2.4)

The integrated model consists of four main components: (1) urban drainage system models for all WWTP-connected areas, (2) an empirical water quality model, (3) a wastewater treatment plant model, and (4) a river model. The urban drainage system is represented using a bucket model, which generates both stormwater and dry weather flow based on sub-catchment-specific parameters such as surface area and population density. A bucket model is a conceptual, volume-based approach that simplifies flow routing by representing parts of the system–such as multiple sub-catchments, pipes, or tanks–as ”buckets” that fill and drain according to inflow, storage capacity, and outflow capacity. This modelling approach captures the basic dynamics of an urban drainage system without requiring expensive, fully hydrodynamic computations.

The final bucket of a catchment feeds into the empirical water quality model developed by Langeveld et al. (2017). This model generates pollutant concentrations/loads as a function of flow, upstream tank filling degree, and time of day, more on this in Section 3.1.2. The resulting flow and pollutant loads are passed to a detailed WWTP model described in Weijers et al. (2012) as influent, where the waste and stormwater are treated and discharged as effluent into the receiving waters. The river model receives inputs from both WWTP effluent and additional stormwater inflows, including surface runoff and combined sewer overflows. Water quality in the river is modelled throughout different river sections. The integrated model was originally developed by Weijers et al. (2012). Since the model was created, the treatment plan has undergone upgrades, including the installation of additional aeration systems between 2016 and 2018. As a result, while the dissolved oxygen levels in the effluent since the upgrade meet satisfactory standards, any dissolved oxygen-related outputs from the 2012 model are no longer representative of present-day conditions and are therefore not thoroughly considered.

The hydrodynamic model enables detailed simulation of flow within its conduits generated by precipitation and wastewater, based on an accurate hydraulic representation of the Geldrop catchment. Notably, it includes the transport pipeline connecting the Aalst pumping station, Geldrop catchment and the Mierlo catchment to WWTP Eindhoven. This pipeline has a significant buffer volume and transport time, making it a critical component for analysing dry weather flow buffering effects. For this reason, it is implemented fully hydrodynamically in the later stages of the study.

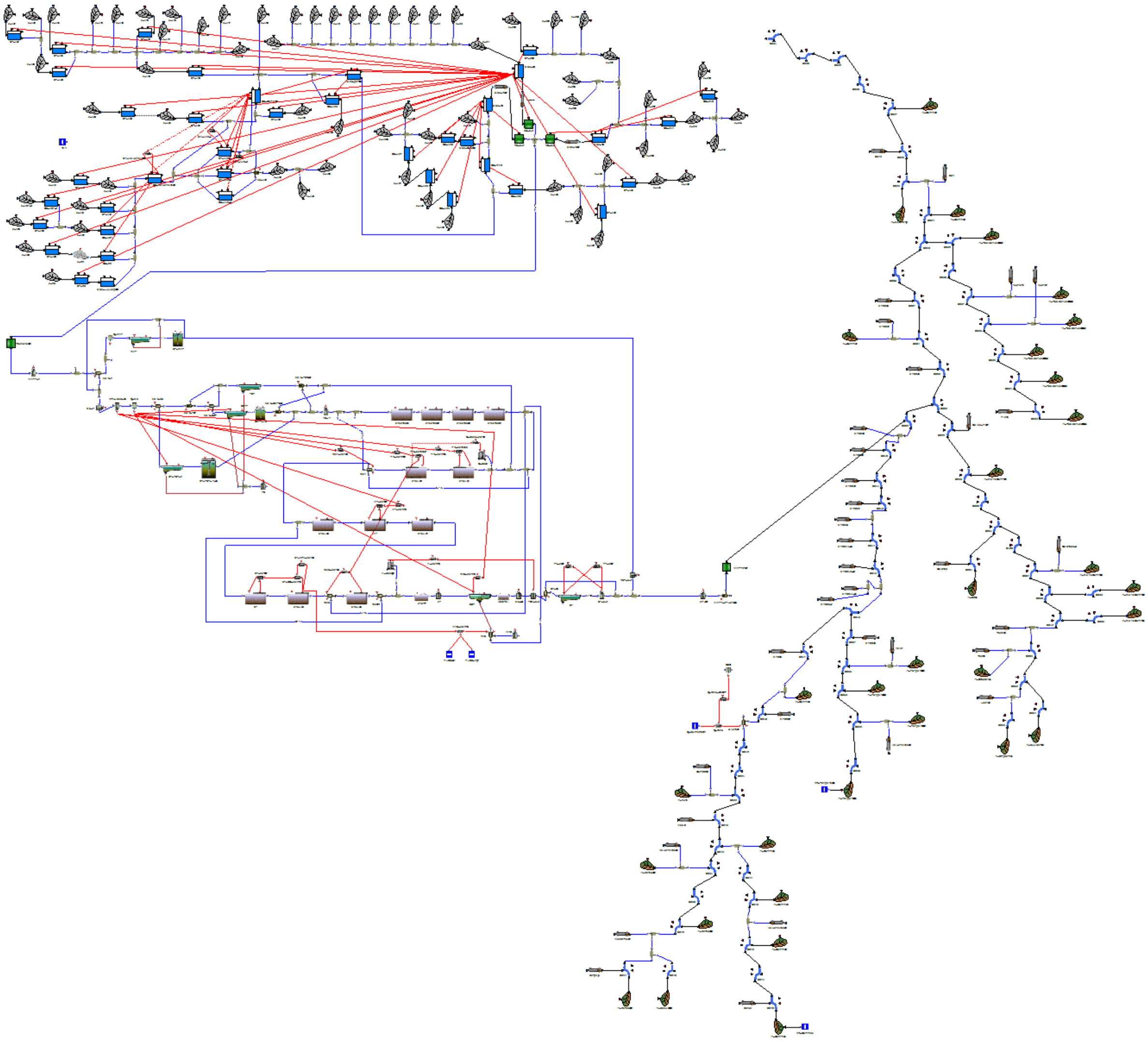


Figure 2.3: The integrated model of the urban wastewater system of Eindhoven, implemented in WEST by DHI (Vanhooren et al., 2003)

Figure 2.4: The full hydrodynamic model of Geldrop, as presented in Storm Water Management Model by EPA (Rossman et al., 2010)

3
Methodology

This chapter presents the methods used to achieve the research objectives. It begins by describing the setup of the required systems and data sources. Then, the first research question introduces a method for analysing the case study's urban wastewater system's characteristics and capacities. The chapter then outlines the implementation of RTC for managing dry weather flow using perfect weather forecast data. This approach is then extended by incorporating ensemble-based forecasts to replace the perfect forecast data. The presented data and methods will be provided open-source in a public web repository (https://github.com/jipsteiger/Effects-of-In-Sewer-Buffering-of-DWF-on-Surface-Water-Quality).

3.1. Modelling Structure

In this thesis, various models and datasets are used in a combined fashion to generate the desired results. In total, three different models, two datasets, and two scripts are used (Figure 3.1). How these systems are generated, used, and relate to each other is described in this section. The implemented system architecture consists of 5 parts: a bucket model of the urban drainage network, the water quality model, the wastewater treatment model, the real-time control script, and precipitation-related data. This research builds an urban drainage bucket model, which summarises a group of conduits and subcatchments into a representative storage unit and subcatchment based on existing sources, and it develops a real-time control script to actuate pumps based on available precipitation and UDS hydraulic data. Because, in general, UDS modelling software lacks adequate water quality modelling capabilities (Jia et al., 2021), a separate water quality model predicts pollutant levels. The model then sends the calculated pollutant loads to a wastewater treatment model to generate effluent data; exact dataflows are detailed in Figure 3.2 and Section 3.1.4.

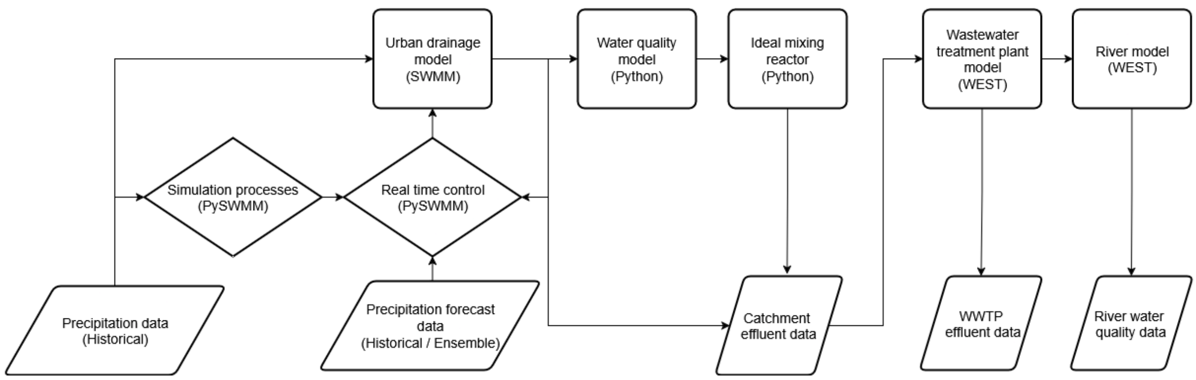


Figure 3.1: Real-time control and evaluation data system architecture

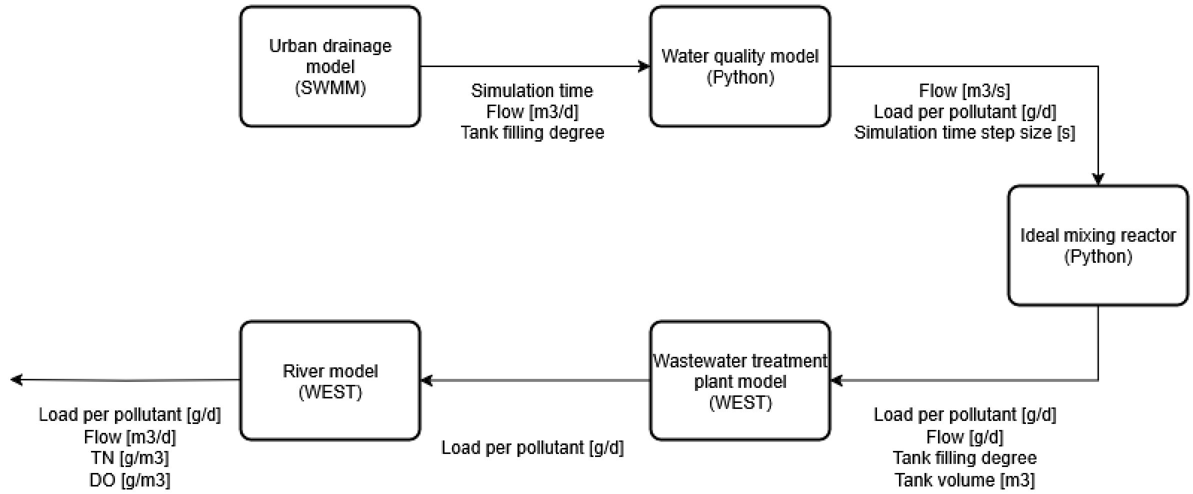


Figure 3.2: Flow diagram detailing the exact flow of different sets of data between the various models used in this project

3.1.1. Urban Drainage Model

Urban drainage models generally mimic real-world drainage infrastructure behaviour by accurately modelling subcatchments that drain into a single 'node', which are connected by conduits that represent their real-life counterparts. Based on these networks, accurate hydraulic loads in the system can be modelled to analyse the system's outflow, flooding, and overflow characteristics. For the development of the urban drainage model in this thesis, hydraulic modelling software is required to capture key processes such as storage utilisation, flow routing, and sewer overflow behaviour. United States Environmental Protection Agency Storm Water Management Model v5.2 (SWMM) (Rossman et al., 2010) is a widely used open-source program and fits these requirements. Its Python wrapper, Python Interface To Storm Water Management Model v2.0.1 (PySWMM), enables interaction with the model during simulation (McDonnell et al., 2020), allowing for easy control-rule manipulation during simulation.

Moreover, a bucket model is used instead of creating a model that captures each node and conduit, which is highly complex and expensive to run. It is a simplified, conceptual representation of how both rainfall and wastewater move through the UDS. Such a model is commonly used to reduce simulation time by reducing the complexity of UDS while maintaining accuracy through calibration (van Daal-Rombouts et al., 2016; Wolfs et al., 2013; Coutu et al., 2012). It aggregates multiple nodes and conduits into a single element, combining all storm and wastewater generating components, storage capacity, and drainage into a single representative element. Several elements are then connected by a pump with a representative flow capacity, which eventually leads to the outflow of the catchment. In this thesis, the urban drainage model represents each major catchment that contributes to the WWTP inflow with an individual bucket model using a set of sub-catchments, storage tanks, CSOs, and (exit) pumps representing the outfall point. This structure follows the WEST model's structure.

Sub-Catchments

In this research, sub-catchments are defined as representative smaller sections (i.e., buckets) of each catchment (Eindhoven, Geldrop, Mierlo, or upstream of Aalst). Each sub-catchment is characterised by a combination of specific and universal parameters. The sub-catchment-specific parameters define the flow-generating characteristics, such as wastewater or stormwater. The universal parameters are applied uniformly across all sub-catchments, either because the available WEST-based data specified them as such or due to a lack of sub-catchment-specific data.

- Sub-catchment specific: population density, area, wastewater flow per inhabitant, industrial flow, storage capacity, associated DWF flow pattern, flow accumulation delay, and assigned rain gauge
- Sub-catchment universal: depression storage, evaporation pattern, percentage of impervious area,% of impervious area without storage, slope, and infiltration method

Universal parameters, when not originally specified, are determined by comparing different parameter configurations across outflows of multiple sub-catchments against the outflows of the same subcatchments in the reference WEST model. The best fit is established by manual adjustment and visual fitting through overlapping of subcatchment outflow time series of existing model data and new SWMM model during storm events. The resulting values are assigned globally to all sub-catchments and are summarised in Appendix A.1

To create an effective bucket model, a sub-catchment is split into two distinct sections: its flow-generating part and its storage capacity. A bucket model separates the storage component from each sub-catchment to aggregate the storage of all subcatchments into a single large storage unit located at the downstream end of the catchment. The UDS modelling software, SWMM, divides the flow-generating part of each sub-catchment into two components: wet weather flow and dry weather flow. A schematic overview of this is shown in Figure 3.3. The sub-catchment in SWMM defines the wet weather flow based on its specific area, width, assigned rain gauge, and the globally defined parameters mentioned earlier. Case study data provide the sub-catchment area, while the width is initially set in metres equal to the area in hectares (e.g., a 200-hectare area is assigned a width of 200 metres). The width parameter is then further fitted in the same manner to the universal sub-catchment parameters. This manual fitting is performed for sub-catchments over 100 hectares, as these catchments represent close to 90% of all catchment area. The assigned rain gauge, depending on the subcatchment location within the overall study area, determines precipitation based on input values or files for those subcatchments.

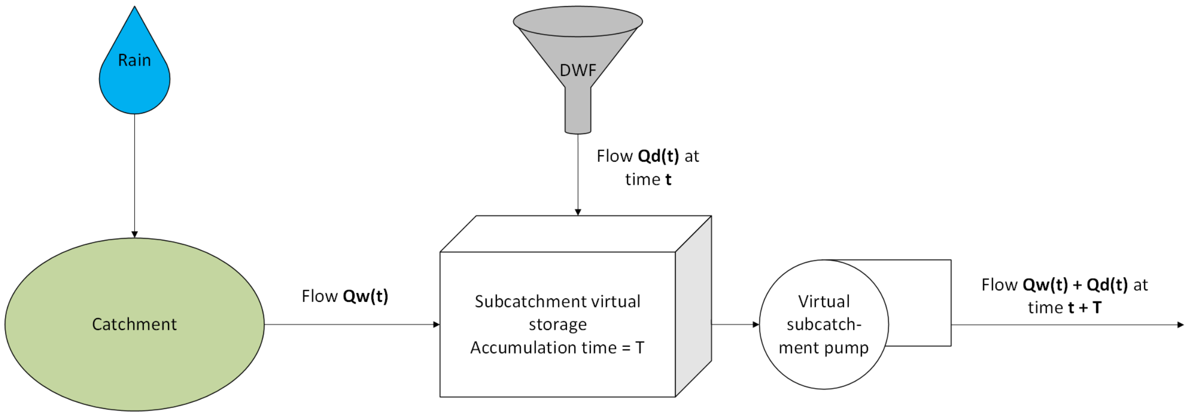


Figure 3.3: Schematic overview of subcatchment design, with a wet weather flow generating part in the form of the catchment, and a dry weather flow (DWF) generating part in the form of the subcatchment virtual storage

The wet weather flow generated by the sub-catchment enters a downstream storage unit, where the dry weather flow is generated. This dry weather flow consists of two components: domestic wastewater and industrial wastewater. The model calculates domestic wastewater using the sub-catchment area, population density, and daily wastewater generation per capita and applies diurnal patterns based on location-specific case study data. This pattern includes hourly, weekend, and–when available–daily and monthly variations. Industrial discharge is modelled as a constant flow through the week and year and is introduced as a direct constant inflow into the storage unit.

The model has not yet incorporated the previously mentioned flow accumulation delay. To use this delay, the model uses the introduced storage unit as a virtual buffer with limitless capacity–with any desired shape–to retain both dry and wet weather flows over the duration of the intended delay. This flow delay serves to better replicate the flow regime of a full hydrodynamic model, where travel times through the conduits significantly influence system behaviour. To implement this delay, the model places a pump downstream of the storage unit, which discharges all inflow received at time t at a later time $t + FAD$, where FAD represents the flow accumulation delay (Equation 3.1). A similar approach was described by Schütze et al. (2002). This pump functions as an ideal unit with adequate capacity to handle any volume of incoming flow.

$$Q_{\text{out}}(t) = Q_{\text{in}}(FAD) \tag{3.1}$$

Where:

- $Q_{\text{in}}(t)$: Inflow rate into the storage unit at time t $[\mathrm{L}^3/\mathrm{T}]$
- $Q_{\text{out}}(t)$: Outflow rate from the storage unit at time t $[\mathrm{L}^3/\mathrm{T}]$
- FAD: Flow accumulation delay $[\mathrm{T}]$

SWMM does not support the construction of such buffered storage units. To overcome this limitation, the Python wrapper PySWMM is used. A custom script integrates PySWMM by taking the SWMM model file as input and defining key settings such as the intervention step size, simulation start and end dates, and the report start date. With each intervention step, the script manages the virtual storage unit by actuating the virtual pump to simulate the intended buffering behaviour. During the simulation, the script tracks the inflow to each virtual storage unit. It extracts the delay FAD from the storage unit's name, which includes a numeric value representing the accumulation delay defined by earlier studies. The script then ensures that, after $t + FAD$ minutes, the outflow from the storage matches the inflow that occurred at t minutes, thereby creating the effective delay. Each catchment's downstream pump connects either to another sub-catchment storage unit–with its own corresponding delay–or to the aggregated storage unit of the entire catchment.

Catchment Storage and Combined Sewer Overflow

To represent each catchment's storage capacity and combined sewer overflow behaviour, a single storage unit is introduced at the most downstream location of each catchment. This storage unit aggregates all upstream storage capacity into a single volume. Both the catchment's outflow pump and the weir (which leads to the CSO outfall) connect to this storage unit. The storage units are designed based on only a given volume in available data; therefore, a rectangular shape is chosen, with a width-height ratio that results in a depth of around 10 metres. In case a storage curve is available, the provided storage curve is used instead. The model calculates the weir crest height based on the total catchment storage capacity and storage unit's dimensions (Equation 3.2). The weir discharge coefficient is uniformly set to 120 m^3/s for all weirs, as this provided similar results as available in the reference data based on visual CSO flow and catchment outflow time series analysis.

$$h_w = \frac{V_{\text{catchment}}}{W \times D} \tag{3.2}$$

Where:

- h_w: Weir crest height $[\mathrm{L}]$
- $V_{\text{catchment}}$: Total catchment storage volume $[\mathrm{L}^3]$
- W: Storage unit width $[\mathrm{L}]$
- D: Storage unit depth $[\mathrm{L}]$

The maximum storage depth is calculated from the calculated weir crest height; the maximum depth is a rounded-up value from the crest height (e.g., from 2.5 to 3, or from 25 to 30 metres)–while maintaining the calculated crest height–to prevent immediate flooding. Each catchment storage receives inflow from the outgoing pump of one or more upstream subcatchments and discharges flow through either the pump(s) or the outfall. The outfall represents the combined sewer overflow. An overview of this configuration is provided in Figure 3.4.

Catchment Pumps

Catchment pumps are introduced to empty each catchment storage. These pumps drain the storage and are characterised by either a maximum pump rate or a pump curve to provide a realistic catchment outflow based on the upstream connected storage unit's storage depth levels. Each catchment's storage is drained by one or more pumps with real pump characteristics, categorised as either exit pumps or intermediate pumps. Exit pumps transport flow from the downstream end of a catchment to the WWTP inflow, while intermediate pumps transfer flow between catchments or to a transport pipe.

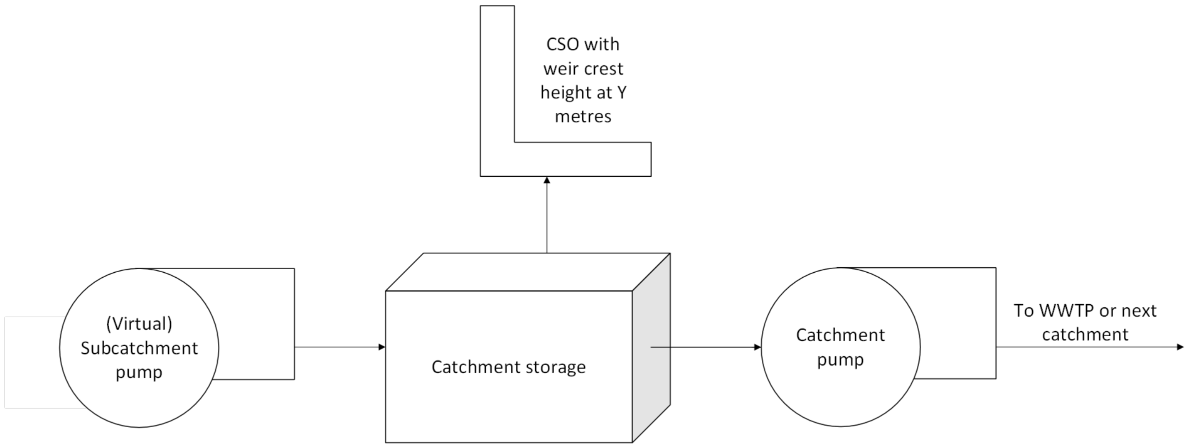


Figure 3.4: Diagram of basic main catchment storage unit setup. Including incoming virtual sub-catchment pumps, the main catchment combined sewer overflow (CSO), and the outgoing pump from the catchment

Pump curves are assigned to the exit pumps to define flow rates based on the upstream storage water depth. Intermediate pumps are configured as ideal pumps, with maximum capacities. Both pump configurations are derived from available case study data. Only the exit pumps are actively controlled in this research.

To control the exit flows to the WWTP using RTC, pump target values are dynamically set during the simulation. These targets are defined as a scalar multiplier, representing the ratio between the desired flow and the flow determined by the pump curve at the current upstream water level. This dependence of the target setting on varying upstream depths introduces complexity in determining the appropriate target setting throughout the simulation. To simplify control and ensure consistent outflow behaviour, the exit pumps are instead implemented as ideal pumps with a maximum flow capacity of 10 m^3/s. This approach allows the script to calculate targets relative to the fixed upper limit, making control decisions independent of upstream water levels. When active pump control is disabled, the script can compute a target value based on the internally saved pump curve data and current upstream water level to replicate regular pump curve behaviour.

Exceptions

While most of the urban drainage system can be modelled using the three methods described above, some (sub)catchments require additional steps for more realistic model behaviour. For example, Figure 2.4 shows how the large central catchment (Geldrop itself) discharges to two points in the transport pipe. In such a case where a catchment discharges to two or more distinct downstream locations, the outgoing intermediate pump from the catchment is not connected directly to a downstream node, but instead to a virtual node. This virtual node then connects to the various downstream locations through a set of ideal virtual pumps. The script assigns a set flow distribution across these pumps based on an analysis of both the characteristics of the catchment and receiving locations, or available distribution values. Since SWMM does not natively support this type of configuration, the simulation script handles the additional logic. For each outgoing virtual pump, the script calculates the target setting based on the inflow to the virtual node, the desired pump fraction, and the maximum pump capacity (Equation 3.3).

$$TS_i = f_i \times \frac{Q_{\text{node}}}{Q_{\max,i}} \tag{3.3}$$

- TS_i: Target setting for pump i [-]
- f_i: Assigned flow fraction for pump i [-]
- Q_{node}: Total inflow volume rate to the virtual node $[\mathrm{L}^3/\mathrm{T}]$
- $Q_{\max,i}$: Maximum flow capacity of pump i $[\mathrm{L}^3/\mathrm{T}]$

Larger, more complex catchments can experience reduced model accuracy due to the simplifications inherent to bucket models. Adding back the storage units, pumps, and CSOs, as was in the WEST model, to one or more sub-catchments helps mitigate this loss of accuracy (Figure 3.5). Adding storage capacity within sub-catchments reduces the total storage capacity in the main catchment storage unit. The storage units and CSOs follow the same calculation procedures as those applied at the catchment scale, while pumps are assigned capacities that reflect real-world conditions.

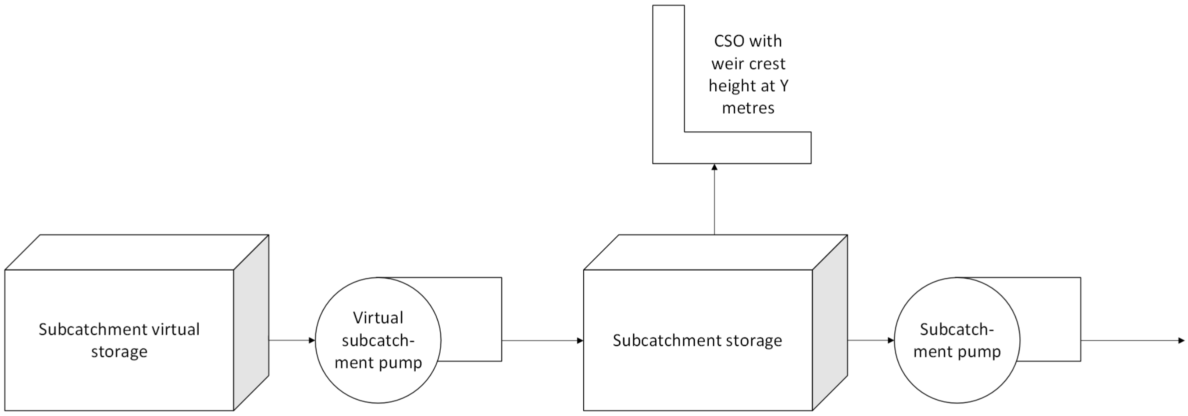


Figure 3.5: Sub-catchments with additionally implemented subcatchment storage, combined sewer overflow (CSO) and pump.

In more complex scenarios, the two methods described above can be combined, allowing a single pump–either at the catchment or sub-catchment level–to distribute flow into three distinct storage units. Each of these storage units can have its own CSO and dedicated pump. Additionally, the transport pipe connecting Riool Zuid is added to the model to provide more realistic storage behaviour in this section. The exit pumps of the three catchments connected to this transport pipe have their outflow point connected to the different locations in the transport pipe, rather than directly to the treatment plant inflow point.

Resulting Model and Testing

The model incorporates 4 rain gauges, 54 sub-catchments, 15 combined sewer overflows, and 44 conduits. It also includes 6 storage units and 10 pumps. A schematic overview is provided in Appendix Figure B.1. Since a reference model exists, the outflow of the newly created SWMM model can be directly compared to the outflow of the baseline WEST model. Model performance is evaluated both visually and using two quantitative metrics: the Nash-Sutcliffe Efficiency (NSE) (Nash and Sutcliffe, 1970) and the Root Mean Squared Error (RMSE). The NSE measures how well the SWMM model replicates the outflow produced by the WEST model, with values typically ranging from $-\infty$ to 1, where 1 indicates perfect model replication. The RMSE quantifies the average deviation in flow between the two models, with a value of 0 representing a perfect match. Performance results are presented separately for the Eindhoven and Riool Zuid catchments.

3.1.2. Water Quality Model

Since, as mentioned previously, UDS modelling softwares, such as SWMM, lack adequate water quality modelling capabilities, a third-party water quality model is required. The WEST model, which is used as both calibration for the modelled UDS and as a WWTP model, uses such a water quality model already, namely the Empirical Sewer Water Quality Model from Langeveld et al. (2017). Since this thesis will make use of the treatment plant model in WEST, five pollutant loads are required to run this treatment plant model: particulate COD, dissolved COD, TSS, NH_4, PO_4. The treatment plant model fractionates these five pollutants into the required parts to run the model. These five pollutant loads are generated by the Empirical Sewer Model, based on flow, filling degree, and time of day. As this Empirical Sewer Model is already fully calibrated for the used catchments and their characteristics in this project, and provides the required pollutant loads for the treatment plant, this model is also used in this project.

Rather than using the already implemented water quality model developed for the Kallisto project in WEST, the model is recreated in Python to allow for more flexibility and control. The logic for this custom block, written in mIRC scripting language (mSL), was extracted from the WEST model and converted to Python logic. Both Eindhoven and Riool-Zuid are assigned a calibrated model instance, with catchment-specific calibrated parameters (taken from the reference WEST model) of average pollutant concentrations, pollutant patterns, storage threshold, flow thresholds for distinction between small and medium storm events, water depth threshold, and a 95th percentile dry weather flow diurnal pattern. During simulation, the model determines the current flow scenario based on inflow, storage filling degree, and time of day. Each pollutant, with the exception of TSS and particulate COD, which differ slightly, follows the exact same steps to determine the pollutant load level, primarily based on DWF flow and level of stormwater dilution. When both flow and filling degree remain below the DWF threshold, standard dry weather concentrations are applied ("process 1"). If water depth remains below the threshold but flow exceeds the DWF threshold, small event dilution and restoration are triggered ("process 6"). When flow exceeds both the DWF and event thresholds while water depth is below the depth threshold, the model activates processes representing medium dilution, onset dilution, first flush, and recovery ("processes 2, 3, 4, and 5"). Finally, when water depth exceeds the set threshold–indicating a large event–the same dilution and recovery processes are applied (Figure 3.6) (Langeveld et al., 2017).

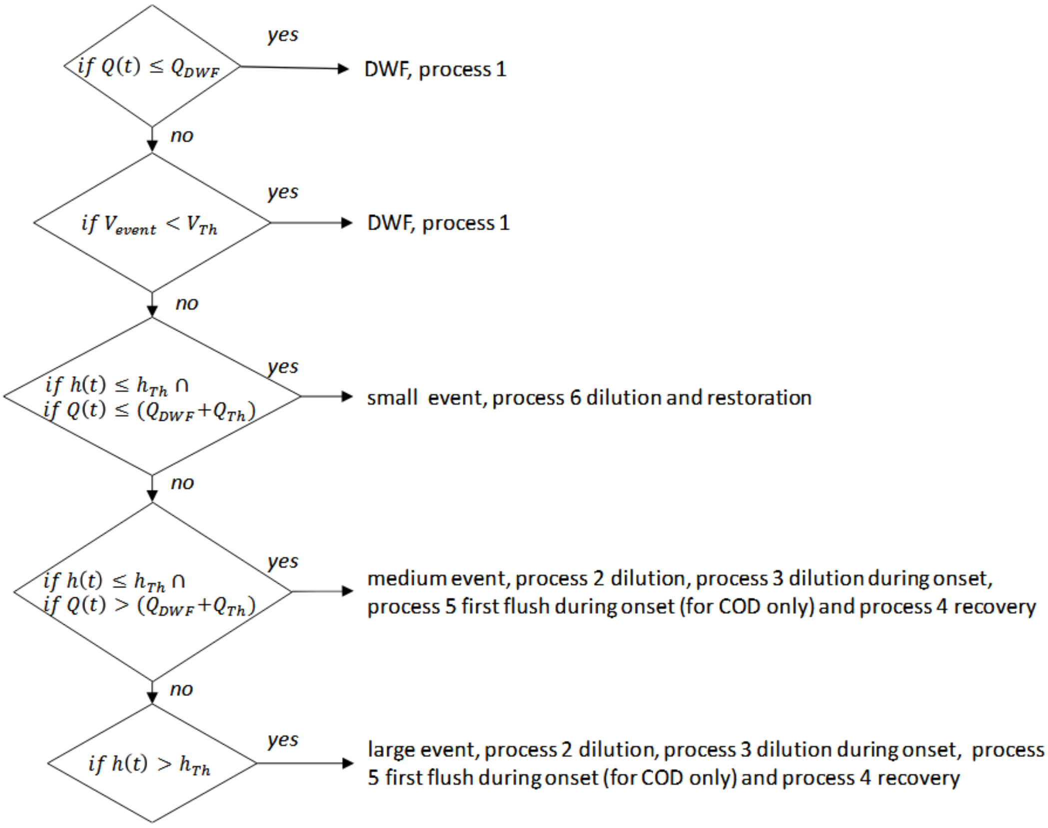


Figure 3.6: Storm event level selection based on flow rate (Q), stored volume (V), storage water depth (h), and thresholds (τ), to determine pollutant dilution levels. Taken from Langeveld et al. (2017)

In an uncontrolled UDS model, the water quality model is typically placed at the exit pumps to calculate pollutant loads based on the undisturbed flow regime (Figure 3.7). However, since this research actively alters the flow at the exit pumps, applying the water quality model in that location would produce non-representative results. This is due to flow buffering, which causes delays and mixing of pollutant concentrations over time. Therefore, the water quality model is moved upstream–before each of the storage units connected to exit pumps–to calculate pollutant loads on the undisturbed incoming flow (Figure 3.8). These loads can then be delayed and mixed within the storage unit while keeping track of concentrations within the storage.

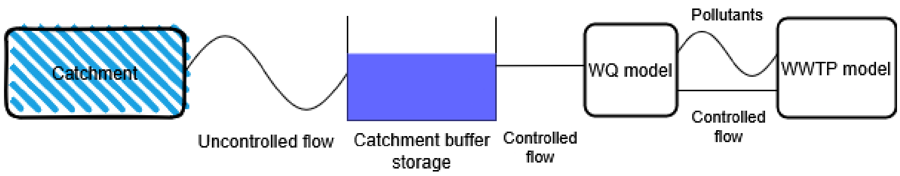


Figure 3.7: Setup and impacts of water quality model (WQ model) location on wastewater treatment plant (WWTP) influent in WEST and during uncontrolled circumstances

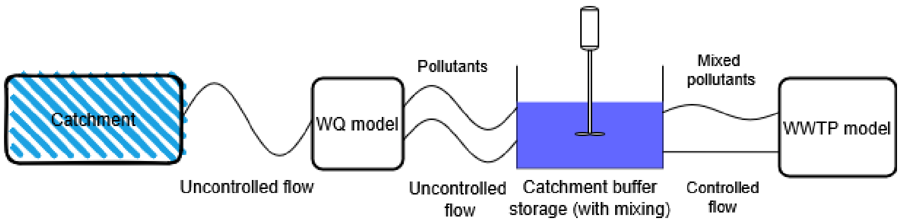


Figure 3.8: Setup and impacts of water quality model (WQ model) location on wastewater treatment plant (WWTP) influent in relocated position for use during real-time control and buffering

Pollutant loads are now calculated upstream of each storage unit using the downstream storage unit's inflow, filling degree, and the current simulation time. The resulting pollution loads are added to the inflow entering the storage unit. Each storage unit is modelled as a fully mixed reactor, characterised by its internal pollutant concentration and stored volume. Pollutant loads are first converted to mass based on the simulation time step size and then added to the internal mass of the storage unit. Simultaneously, the inflow is converted to total incoming volume using the time step size to update the internally stored water volume. The internal concentration is then determined by dividing the total pollutant mass by the current volume and is stored as part of the system state. Outgoing pollutant loads are calculated based on the stored internal concentration and the unit's outflow. Finally, the stored volume is updated by subtracting the outflow volume, again based on the time step size and outflow (Equation 3.8).

$$M_{\text{in}} = C_{\text{in}} \times Q_{\text{in}} \times \Delta t \tag{3.4}$$

$$V_{t+1} = V_t + Q_{\text{in}} \times \Delta t - Q_{\text{out}} \times \Delta t \tag{3.5}$$

$$M_t = C_t \times V_t \tag{3.6}$$

$$M_{t+1} = M_t + M_{\text{in}} - C_{\text{out}} \times Q_{\text{out}} \times \Delta t \tag{3.7}$$

$$C_{\text{out}} = C_{t+1} = \frac{M_{t+1}}{V_{t+1}} \tag{3.8}$$

Where:

- M_{in}: Pollutant mass inflowing to storage unit $[\mathrm{M}]$
- C_{in}: Pollutant concentration of the inflow $[\mathrm{M}/\mathrm{L}^3]$
- Q_{in}: Inflow volume rate $[\mathrm{L}^3/\mathrm{T}]$
- Δt: Time step size $[\mathrm{T}]$
- V_t: Volume inside the storage unit at time t $[\mathrm{L}^3]$
- V_{t+1}: Volume inside the storage unit at time $t+1$ $[\mathrm{L}^3]$
- Q_{out}: Outflow volume rate $[\mathrm{L}^3/\mathrm{T}]$
- C_t: Pollutant concentration inside the storage unit at time t $[\mathrm{M}/\mathrm{L}^3]$
- M_t: Total pollutant mass inside the storage unit at time t $[\mathrm{M}]$
- M_{t+1}: Total pollutant mass inside the storage unit at time $t+1$ $[\mathrm{M}]$
- C_{out}: Pollutant concentration of the outflow at time t, equal to the storage concentration C_{t+1} $[\mathrm{M}/\mathrm{L}^3]$

3.1.3. Precipitation (Forecast) Data

This thesis includes an analysis of the effects of uncertainty in precipitation forecasts on RTC (and WWTP) performance. This analysis is performed by comparing the results using ideal, perfect forecasts containing no uncertainty and using forecasts with inherent uncertainty, emulating forecasts used in a real-world scenario. For this reason, two types of datasets are used: observed precipitation and an ensemble of precipitation forecasts. The observed precipitation dataset serves three purposes: providing input to the urban drainage system for precipitation rates, determining current rainfall conditions within the RTC script, and acting as a perfect weather forecast for the second research question. The ensemble forecast dataset is employed in the third research question to replace the perfect forecast to more realistically simulate real-world conditions.

The precipitation data is required to have a 5-minute accumulation interval, as this provides a more realistic rainfall pattern for the urban drainage model, rather than hourly or monthly totals to then spread these evenly over each time step. Additionally, both datasets must cover the same geographic area and span the same long time frame to ensure the ensemble forecasts fully correlate with the observed precipitation data. The Royal Netherlands Meteorological Institute Data Platform (van Infrastructuur en Waterstaat, 2025) offers both such datasets publicly. Specifically, the "Precipitation - 5 minute precipitation accumulations from climatological gauge-adjusted radar dataset for The Netherlands (2.4 km) in KNMI HDF5 format" serves as the observed precipitation dataset, while the already deprecated "Ensemble precipitation forecasts made with Quantile Regression Forests and deterministic Harmonie-Arome inputs" provides the ensemble forecast data with a 1-hour resolution. Since March 2025, this deprecated dataset has been replaced by a new one that only contains data from 2025 onwards.

The forecast dataset covers the extended summer period for each available year, from March 15th to October 15th. Accordingly, all data for the year 2024 were downloaded for both datasets. The observed precipitation dataset has a 5-minute accumulation interval, with grid cells measuring approximately 2.4 by 2.4 km. The ensemble dataset provides forecasts every 6 hours, each predicting precipitation for the following 48 hours, with a 1-hour resolution. For each forecast hour, 50 ensemble members generate precipitation predictions on a 7.5 by 7.5 km grid. Based on the case study's catchment layout, specific regions are designated to be represented by rain gauges in the urban drainage model (Table 2.2). Each rain gauge is assigned a corresponding coordinate area, from which data is filtered and saved from both datasets for later use. If a single region is covered by 2 or more grid cells, the values per grid are aggregated by taking the mean of the values per grid. To make the ensemble-forecast data easier to read, it is saved as a comma-separated values file, with the following columns:

- **Region:** refers to which rain gauge region the ensemble forecasts belong to
- **Date:** contains date and time when the 48 forecast predictions are made, in 6-hour intervals
- **Date of forecast:** relates to the 48 forecast dates and times, with each forecast containing 50 ensemble members
- **Ensembles:** contains the 50 ensemble members per date of forecast

Data Availability

At every intervention time step in the simulation (5 minutes), forecast data is read when available, to make a decision as to what control step is to be taken next. Having complete datasets is ideal; a few scattered data gaps are allowed. Therefore, the retrieved precipitation and precipitation forecast datasets are analysed for completeness. A preliminary visual assessment is also performed to explore the relationship between forecasted and observed precipitation levels. The historical precipitation dataset requires a value of rainfall accumulation every 5 minutes for each of the regions. The structure of the forecast dataset, which includes four forecasts per day–each projecting up to 48 hours ahead–should contain a total of 188 files per day (i.e., 47 forecast steps per forecast x 4 forecasts per day). It is assumed that if a forecast file exists, it contains predictions for all relevant catchments. The historical precipitation dataset is found to be complete over the selected period; each designated region had a recorded rainfall depth value for every time step. The overall availability of ensemble forecast data is illustrated in Figure 3.9.

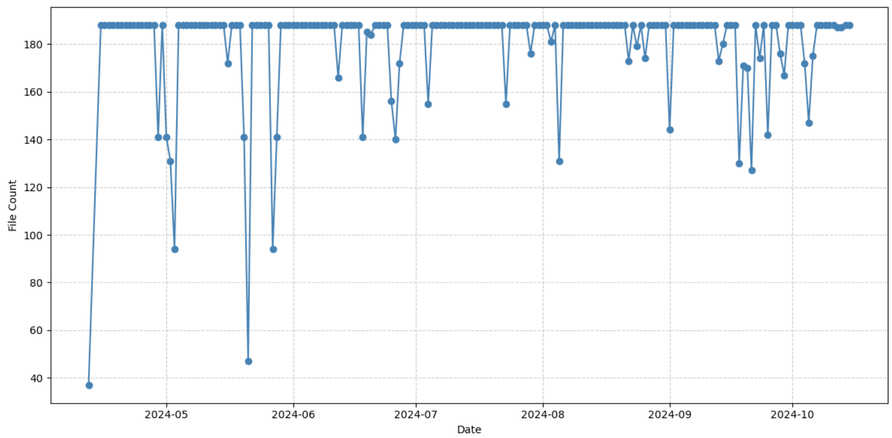


Figure 3.9: Number of ensemble-forecast files available per day, where the desired number of files per day is 188

The overall ensemble forecast data availability varies over time, with no clear pattern identified. The absence of data at the first time point (March 12th) is attributed to its position outside the defined extended summer period, which begins on March 15th–the period for which the dataset was created. For the remaining missing data, no clear explanation is found, as the corresponding file did not appear to exist in the source database. Nevertheless, the overall completeness of the dataset–assuming 188 files per day–is 96.2%, which is deemed sufficient for the intended analysis.

Forecasting Performance Analysis

Forecast performance is analysed, at a later stage, by running both (using perfect weather forecasts and ensemble weather forecasts) RTC scripts once, while saving the respective predictions per catchment. This resulted in a dataset where, for each hour between March 15th and October 15th, per catchment, a perfect yes/no and an ensemble yes/no prediction is registered. Based on these results, two types of evaluations are performed:

1. **Hourly Confusion Matrix:** For each catchment (Eindhoven and Riool Zuid), the hourly predictions from the ensemble forecasts are compared against those from the perfect forecast. By entering the perfect forecasts as the 'truth', and the ensemble forecasts as the 'predictions', and calculating a confusion matrix from this using Scikit-learn's confusion matrix method (Pedregosa et al., 2011).
2. **Event-based Confusion Matrix:** Rain events are identified as continuous periods of predicted "yes" (i.e., rain) using connected event labels. An event from the ensemble prediction (can span several hours) is considered a true positive if it overlaps in time with any event in the perfect prediction (can span several other hours). False negatives are events in the ensemble forecast that do not overlap with any forecasts based on the historical dataset, while false negatives are perfect forecasts that are missed by the ensemble. Lastly, true negatives are identified as overlapping dry periods in both predictions. Based on this, a confusion matrix is also created for analysis.

3.1.4. Flow of Data Between Models

With the resulting WWTP influent data from the created urban drainage model, water quality model, and precipitation data, WWTP effluent can be calculated using the WEST model. Originally, this model included an integrated urban drainage system, which supplied flow data to the water quality model, subsequently feeding load data into the WWTP pollutant model. However, both the UDS and water quality model components have been removed to support RTC by means of the SWMM model, therefore requiring external input to drive the WWTP model (Figure 3.2).

The script provides time-step-based output for each exit pump, including flow, pollutant loads, and catchment storage unit filling degree. These outputs are used as input files in WEST. To control the WWTP, the model originally depended on data from the now-removed UDS, specifically the flow and filling degree. These parameters are now directly linked from the input files to the relevant control units.

To process the remaining flow and pollutant input in WEST, all data from the various catchments are aggregated into a single flow and load variable, which gets sent to the WWTP input as a single variable. This aggregation requires all variables–per catchment–to be in a single list, rather than individual parameters. The input file, read by an input block, is only able to give individual values. A combining block is therefore introduced, that combines, for each catchment, all six values-5 pollutants and one flow–into a single list; this list is then passed onto the aggregation block.

3.2. System Characterisation for Real-Time Control Input

With the proposed goal of flattening the dry weather flow to the treatment plant, it is important to first understand the characteristics of the urban drainage system. For this, the first research question was introduced: How does the current system behave in various scenarios, and what are the current RTC-relevant characteristics of the system? This question is answered by performing two analyses.

- To what degree can the effluent of the treatment plant be improved by having a constant influent flow?
- What is the time required to discharge all stored wastewater?

3.2.1. WWTP Effluent Sensitivity Analysis

The first sub-question, "As to what degree can the effluent of the treatment plant be improved by having a constant influent flow?" is answered using three scenarios, with different influent characteristics. The question is split into 2 analyses: analysing the current regular system behaviour for understanding and later comparison, and quantifying the maximum gain in effluent quality with perfect constant influent flow.

Scenarios:

1. Extended summer period with diurnal wastewater and precipitation
2. Extended summer period with diurnal wastewater only
3. Extended summer period with constant wastewater only

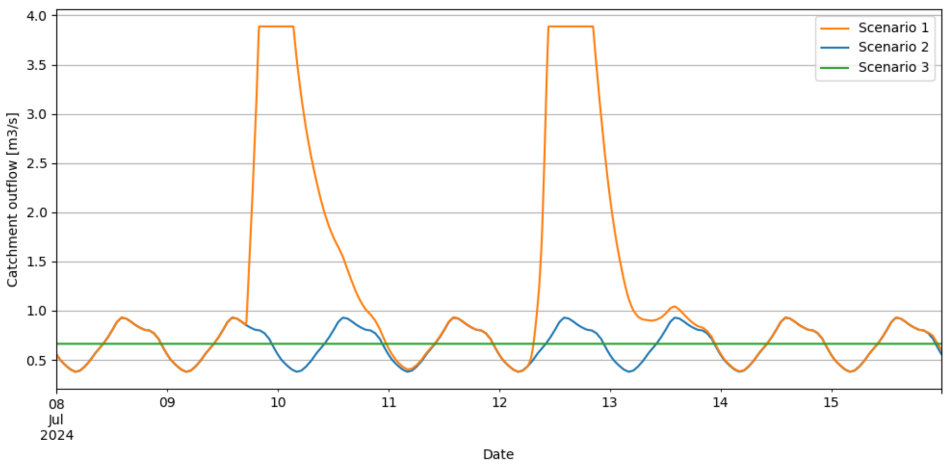


Figure 3.10: Wastewater treatment plant influent flow under the three different scenarios

The scenarios establish baseline values for the system in uncontrolled circumstances (scenario 1), allowing for direct comparison with the later added RTC. The comparison between scenarios 2 and 3 showcases the maximum potential the system has during dry weather circumstances in improving WWTP effluent and river water quality when flattening WWTP influent flow. The second scenario is created by using a model with no precipitation present. Scenario 1 utilises the observed precipitation data as input for precipitation. Scenario 3 builds on scenario 2 by fixing all exit pump flows to a constant value, corresponding to the average daily flow (no variation in weekly or monthly flow is present in this case study). This approach generates 3 x n datasets–where n is the number of exit pumps–that serve as input for the WWTP model. The WWTP model then produces effluent data, which is analysed using objective functions introduced later in Chapter 3.3.2.

3.2.2. Required Time to Empty Wastewater Storage

Understanding the system characteristics is important since the temporary storage of wastewater in the sewer system reduces the available stormwater storage capacity and may worsen the negative impacts of combined sewer overflows. In the worst-case scenario, this buffering could result in more frequent, larger volume, and more pollutant-rich CSO events. Determining how long it takes to discharge all stored wastewater to the treatment plant and what peak discharge causes problems for the treatment process is important to know how far ahead of time forecasts are required.

The increased risk of CSO overflows is mitigated by implementing heuristic rules that take into account the weather forecast to pre-emptively empty the buffered wastewater. The exit pumps will then, in addition to the constant wastewater outflow, pump extra to empty the storage volume. First, the maximum buffer capacity, in regular constant outflow conditions, is determined. Afterwards, an analysis of how long it takes to drain V volume with Q additional pump flow follows. The insights from this analysis provide a more informed starting point for designing and implementing the associated control rules.

Moreover, to avoid placing excessive stress on the WWTP, this additional pump capacity is limited to the mean daily flow. The mean daily dry weather flow is the ideal outflow rate during dry weather. The maximum buffer volume for each catchment is determined by comparing the flows from Scenario 1 and Scenario 3. In this calculation, scenario 1 represents the inflow into the buffer, while scenario 3 represents the constant outflow. By tracking the net difference between these two over time, the stored buffer volume is computed, resulting in a repeating volume pattern for each catchment. To determine the time required to drain this volume, a range of possible additional pump flow values is considered–ranging from 0.01 m^3/s up to mean daily flow. These flow rates are then combined with a desired set of time durations to calculate the corresponding total volume that can be drained.

3.3. Real-Time Control Design

After having created the system architecture, the urban drainage model, and acquired precipitation (forecast) data, the creation of an RTC strategy can be started. Based on the required time to empty analysis from Section 3.2.2, minimum forecast times are determined, together with the maximum additional pump capacity. The achieved results from the RTC using perfect weather forecasts can be compared to the baseline scenario (1) from Section 3.2.1, and to the later added RTC using ensemble weather forecasts. To start the construction of the RTC logic, first, the to-be-controlled parameter has to be identified, then objective functions are introduced, which determine how well the implemented controls achieve the desired results, and lastly, the control procedure itself is introduced. With the implementation of RTC, only the urban drainage system and its outflow (flow and concentration) are affected; no additional changes to the WWTP model, such as temperature, hydraulic residence, or other controls, are made unless specifically mentioned.

3.3.1. The Controlled Parameter

At the point at which RTC is used, in the Python script, two variables can be controlled: volume of water per unit time or pollutant load per unit time. Whereas a more constant load to the treatment plant is more beneficial, flattening the volume of water per unit time is easier to control. The latter only requires balancing a single parameter, namely flow of water by adjustment of pump target settings based solely on water levels or timings in the network, while balancing of load requires balancing both flow of water and pollutant concentration, requiring both setting pump target settings, but also optimising the concentration levels in the storage tanks. Therefore, balancing load is both more difficult and will not reach the same 'flatness' as balancing of just flow. Consequently, in this project, the volume of water per unit time is controlled. The ideal outflow of water is calculated as the mean flow over a period that captures all relevant flow variability, for each of the exit pumps. This target flow is then actively maintained by adjusting the corresponding exit pump's target setting, as described in Chapter 3.1.1.

3.3.2. Objective Functions

Since this thesis tries to optimise various parameters, objective functions are introduced to quantify the achieved differences. To do so, various objective functions are introduced to best capture the changed dynamics of the system. These functions can be divided into two main categories: operational and performant objective functions. Operational objective functions are volume-based objectives that quantify the direct results of the implemented control logic on the urban drainage system water flows. The performant objective functions quantify how well the control logic improves the pollutant load and concentration situation at both the WWTP influent and effluent, as well as in the receiving surface water.

Operational Objective Functions

The operational objective functions assess how well the implemented RTC performs. It specifically assesses how well the control logic flattens the flow to be more constant, how well catchment storages are emptied at the start of storm events, and if the implemented controls had any impact on total CSO volume. Therefore, four different objective functions are introduced:

1. Outflow variance during non-wet weather mode (Equation 3.9)
2. Storage filling degree at the start of storm events (Equation 3.10)
3. Ratio of ideal flow over time with 5% margin (Equation 3.13)
4. Total combined sewer overflow volume (Equation 3.14)

The first function creates a filter to select all exit pump flow during the dry and transition operational modes (Section 3.3.3). From this filtered flow, the overall variance is calculated. This function is important for identifying any major and consistent disturbances during dry weather, where the flow should be ideally flat. The second function selects of all distinct wet weather mode periods the first time step. The mean filling degree of all these selected time steps is then calculated. Through this, an indication can be given of how well the implemented control logic is able to pre-emptively empty the catchment storages before a storm event hits and thus how well it improves overall storm water storage capacity, and reduces the risk of more (polluting) CSO events.

$$\sigma_Q^2 = \text{Var}(Q(t)), \quad \forall t \in \mathcal{T}_2 \tag{3.9}$$

$$\text{FD}_{\text{start\_WWF}} = \frac{1}{|\mathcal{T}_1|} \sum_{t \in \mathcal{T}_1} FD(t) \tag{3.10}$$

Where:

- $\mathcal{T}_1$: Time steps marking the start of a WWF period [–]
- $\mathcal{T}_2$: Time steps where state is DWF or transition [–]
- $FD(t)$: Filling degree at time t [–]
- $Q(t)$: Outflow at time t $[\mathrm{L}^3/\mathrm{T}]$
- $\mathrm{FD}_{\mathrm{start\_WWF}}$: Mean filling degree at start of WWF periods [–]
- σ_Q^2: Variance of outflow during DWF/transition $[(\mathrm{L}^3/\mathrm{T})^2]$

The third function creates an upper and lower boundary, based on the ideal flow and a 5% margin, then counts the number of time steps within this period, divides by the total number of time steps, and inverts the value. This inversion is made since a lower value equals better performance for all other functions. The duration of constant flow is perfect when this value goes down to 1. Conclusively, this function quantifies the total duration of ideal outflow, indicating how often and how well the implemented controls are able to attenuate the DWF pattern.

$$\text{LowerBound} = \frac{Q^*}{m}, \quad \text{UpperBound} = Q^* \cdot m \tag{3.11}$$

$$r = \frac{1}{N_t} \sum_{t=1}^{N_t} \begin{cases} 1, & \text{if } Q(t) \in [\text{LowerBound}, \text{UpperBound}] \\ 0, & \text{otherwise} \end{cases} \tag{3.12}$$

$$\text{OF}_3 = \begin{cases} \frac{1}{r}, & \text{if } r > 0 \\ \infty, & \text{if } r = 0 \end{cases} \tag{3.13}$$

Where:

- $Q(t)$: Actual outflow at time t $[\mathrm{L}^3/\mathrm{T}]$
- Q^*: Ideal target outflow $[\mathrm{L}^3/\mathrm{T}]$
- m: Margin multiplier (e.g., 1.05 or 1.15) [–]
- $\mathrm{LowerBound}$: Minimum acceptable flow, defined as $\frac{Q^*}{m}$ $[\mathrm{L}^3/\mathrm{T}]$
- $\mathrm{UpperBound}$: Maximum acceptable flow, defined as $Q^* \cdot m$ $[\mathrm{L}^3/\mathrm{T}]$
- N_t: Total number of time steps [–]
- r: Fraction of time steps where flow is within acceptable bounds [–]
- OF_3: Objective function value, defined as the inverse of r if $r > 0$, otherwise infinity [–]

Lastly, the fourth function is introduced to ensure that the controls do not negatively affect system behaviour during wet weather. It calculates the total CSO volume per catchment as a sum of the total spilt volume of all CSOs in a catchment.

$$V_{\text{CSO}} = \sum_{j \in \mathcal{C}} \sum_{t=t_0}^{t_1} Q_j(t) \tag{3.14}$$

Where:

- $\mathcal{C}$: Set of CSO node identifiers [–]
- t_0, t_1: Start and end timestamps of analysis $[\mathrm{T}]$
- $Q_j(t)$: Inflow to CSO node j at time t $[\mathrm{L}^3/\mathrm{T}]$
- V_{CSO}: Total combined sewer overflow volume $[\mathrm{L}^3]$

Performant Objective Functions

The performant objective functions relate the effectiveness of the implemented RTC to pollutant levels at various locations; the two catchment outflows, the combined (of 3 catchments when including Nuenen and Son) influent to the WWTP, the WWTP effluent, and in the closing section of the river (See Figure 2.1). For this, four functions are introduced that check averages and daily maxima of load and concentration. If only the load is available as data, concentration is calculated by dividing the load per time step by the flow per time step. If concentration is available as data, the inverse calculation is performed.

1. Average load (influent / effluent / river) (Equation 3.15)
2. Average concentration (influent / effluent / river) (Equation 3.17)
3. Average of the daily maximum load (influent / effluent / river) (Equation 3.16)
4. Average of the daily maximum concentration (influent / effluent / river) (Equation 3.18)

The average load and concentration are calculated as the mean value over a selected period. This serves two purposes: it quantifies whether or not the treatment plant effluent and surface water quality are on average improved due to the implemented control logic, and it serves as a balance check at the influent location between the RTC strategies, as untreated averages should remain roughly equal. The average of the daily maximum load and concentration quantifies how, on average, the peak load-/concentration of each is changed. Assessing changes in peak values is both important for WWTP efficiency and for water quality purposes to prevent toxic environments.

$$\overline{L_k} = \frac{1}{N_t} \sum_{t=1}^{N_t} L_k(t) \tag{3.15}$$

$$\overline{\max_d L_k} = \frac{1}{D} \sum_{d=1}^{D} \max_{t \in d} L_k(t) \tag{3.16}$$

$$\overline{C_k} = \frac{1}{N_t} \sum_{t=1}^{N_t} C_k(t) \tag{3.17}$$

$$\overline{\max_d C_k} = \frac{1}{D} \sum_{d=1}^{D} \max_{t \in d} C_k(t) \tag{3.18}$$

Where:

- $L_k(t)$: Load of pollutant k at time t $[\mathrm{M/T}]$
- $C_k(t)$: Concentration of pollutant k at time t $[\mathrm{M/L^3}]$
- N_t: Total number of time steps [–]
- D: Number of days [–]
- $\max_{t\in d}$: Maximum over time steps within day d [–]
- $\overline{L_k}$: Average pollutant load over the period $[\mathrm{M/T}]$
- $\overline{\max_d L_k}$: Mean of daily maximum loads $[\mathrm{M/T}]$
- $\overline{C_k}$: Average pollutant concentration over the period $[\mathrm{M/L^3}]$
- $\overline{\max_d C_k}$: Mean of daily maximum concentrations $[\mathrm{M/L^3}]$

Combined Objective Function

To support the later analysis of the effect of different decision-making parameters at large, a combined objective function is introduced that calculates the weighted average of several objective functions. The combined objective function is based on a combination of operational and performant objective functions, namely the following:

1. Storage filling degree at the start of storm events
2. Variance during non-wet weather operational modes
3. Total combined sewer overflow volume
4. Ratio of ideal flow over time with 5% margin
5. Average of the daily maximum load (of each pollutant)

To combine these different objective functions, a weighted sum is used based on importance and to what extent they relate to storm events forecast analysis (Equation 3.19). While a weighted sum approach was used for this evaluation, this method inherently has trade-offs and may miss potential optimal solutions due to subjective biases or non-linearity. An alternative would be to apply Pareto optimisation, which would allow exploration of a range of solutions and trade-offs among competing objectives such as CSO reduction, influent flow flatness, or peak load reduction. This method is, however, more complex to compute and interpret, with additional decision-making required to choose among various Pareto-optimal solutions (Marler and Arora, 2004).

For equal comparison, all individual objective functions were normalised by dividing by the baseline. Weights are assigned based on importance; extra CSOs as a result of different forecast parameters should be avoided; therefore, a weight of 0.4 is assigned. Next, flatness of the WWTP influent is prioritised by giving both variance in flow and duration of constant flow with a 5% margin a weight of 0.15. In addition to flow flattening, effects on peak loads are taken into consideration with a weight of 0.2. Lastly, storage filling degree at the start of a storm event is given little priority, as this is also partly covered by CSO volume, with a weight of 0.1.

$$\text{Combined objective function} = 0.1 * OF_1 + 0.15 * OF_2 + 0.4 * OF_3 + 0.15 * OF_4 + 0.2 * OF_5 \quad (3.19)$$

Where:

- OF_n: the n-th selected objective function [-]

3.3.3. Control Architecture

Having set up the urban drainage model in SWMM, with integration of the Python wrapper PySWMM to allow interaction during simulation, additional control logic can be easily implemented. The previously developed script–handling virtual buffering, flow splitting, and related mechanisms as detailed in Chapter 3.1–serves as a parent framework for the implementation of RTC logic, while keeping all core functionalities of the parent framework intact. With this logic, the outflow of the Eindhoven and Riool Zuid catchment is actively controlled during model simulation by modifying the target settings of the exit pumps. This directly benefits the operational objective functions (with the exception of total combined sewer overflow).

The entire control logic can be summarised in five steps (Figure 3.11), which are executed at each intervention time step during the simulation. At each step, three sets of relevant data are retrieved and updated:

- Current precipitation (1)
- Stored volume in the catchment buffer tanks (2)
- Precipitation forecast for the coming 24 hours (3)

The current precipitation is the hourly rainfall sum per catchment, selected for the ”current” hour in the simulation. The stored volume is retrieved from either the volume of water in the main catchment storage unit (for Eindhoven) or the volume in a set of conduits (for the Riool Zuid transport pipe). Forecasts are derived from the historical datasets (or the ensemble dataset), providing precipitation forecasts up to 24 hours ahead per region.

Based on these retrieved sets of data, the control logic proceeds to the three key steps in the RTC process:

- Detecting whether it is currently raining above some threshold (4)
- Assessing whether rainfall is forecast within a specified time window above some threshold (5.1)
- Executing control actions for the exit pumps (5.2)

Rain detection (Step 4) is based on whether the mean rainfall over the upcoming hour exceeds the threshold of 1 mm. This threshold was chosen such that smaller events, which would not fill the available storage capacity in the drainage system by more than 25%, would not trigger a detection, while bigger storm events would trigger a reaction. For the smaller individual catchments of Riool Zuid, this threshold is adjusted upward using an area factor to ensure that total Riool Zuid stormwater volumes remain comparable.

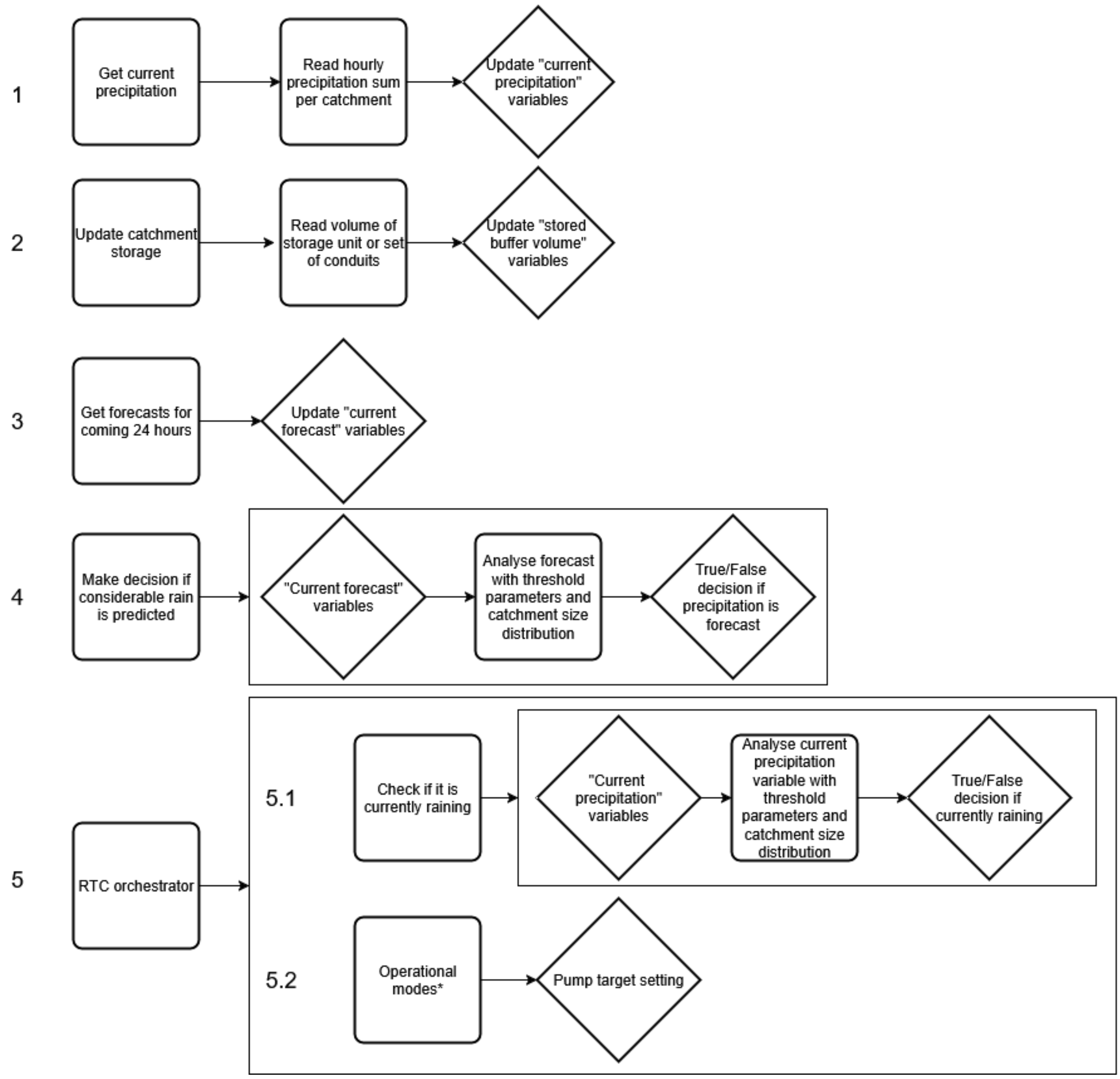


Figure 3.11: Steps within the real-time control (RTC) logic which retrieve and analyse the various required data

Rain is detected for Riool Zuid if either of the following two conditions is met:

1. One of the catchments exceeds the normalized threshold:

$$i \in \textit{GE \& ME}, \textit{RZ north}, \textit{RZ south} \text{ such that } \frac{P_i}{A_i} > \theta \tag{3.20}$$

2. The weighted average precipitation across all catchments exceeds the threshold:

$$\sum_{i \in \{\textit{GE \& ME}, \textit{RZ north}, \textit{RZ south}\}} A_i \cdot P_i > \theta \tag{3.21}$$

$$A_{\text{GE \& ME}} = 0.25, \quad A_{\text{RZ north}} = 0.375, \quad A_{\text{RZ south}} = 0.375 \tag{3.22}$$

Where:

- P_i: Precpitation in catchment i in Riool Zuid over the next hour $[\mathrm{L}]$
- A_i: Area factor as determined in Equaiton 3.22 [-]
- θ: The assigned rain detection threshold to Riool Zuid of 1 mm $[\mathrm{L}]$

This dual-check approach ensures both localised (either in Geldrop (GE), Mierlo (ME), Riool Zuid north (RZ north) or south (RZ south)) and system-wide storms (whole of Riool Zuid, meaning GE, ME, RZ north and south) are detected. Rainfall forecasts (Step 5.1) involve two checks: a short-term and a long-term forecast check. If either forecast exceeds the threshold, rainfall is considered forecasted. Firstly, the short-term check always checks whether the mean predicted rainfall over the next 6 hours exceeds 1 mm (using the same area contribution factors for Riool Zuid as for the precipitation check). Secondly, the long-term check is performed only between 11:00 and 23:00–when buffer storage tends either to start filling, or is already quite full–to enable timely emptying in case of upcoming rainfall. It evaluates the forecasts for the 6-12 hour period ahead, with a limit of up to 02:00 since at that time the buffer storage tends to drain fast, requiring no more additional emptying–effectively making it so that long-term forecasts checks between the hours of 17:00 (11:00 + 6 hours) and 02:00 (Figure 3.12).

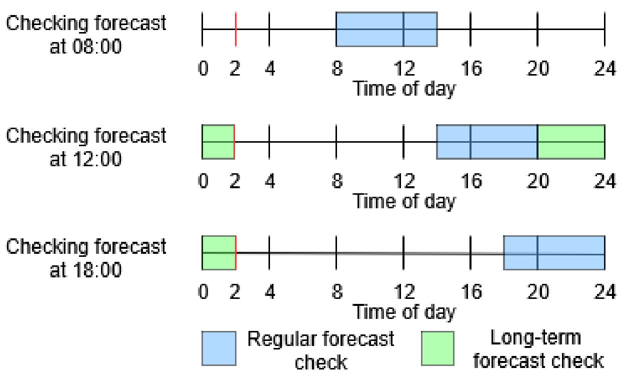


Figure 3.12: Diagram showcasing (long-)term forecast functionality. Specifically, it shows that long-term forecasts do not exceed the 02:00 hours mark (red vertical line)

Step 5.2 is further subdivided into 3 operational modes:

- Dry weather conditions
- A transition phase from dry to wet weather
- Wet weather conditions

The system's operational mode depends on the outcomes of steps 4 and 5.1, as shown in Figure 3.13, which combines flowchart elements and logic gates (further detailed at the bottom of Chapter 3.3.3).

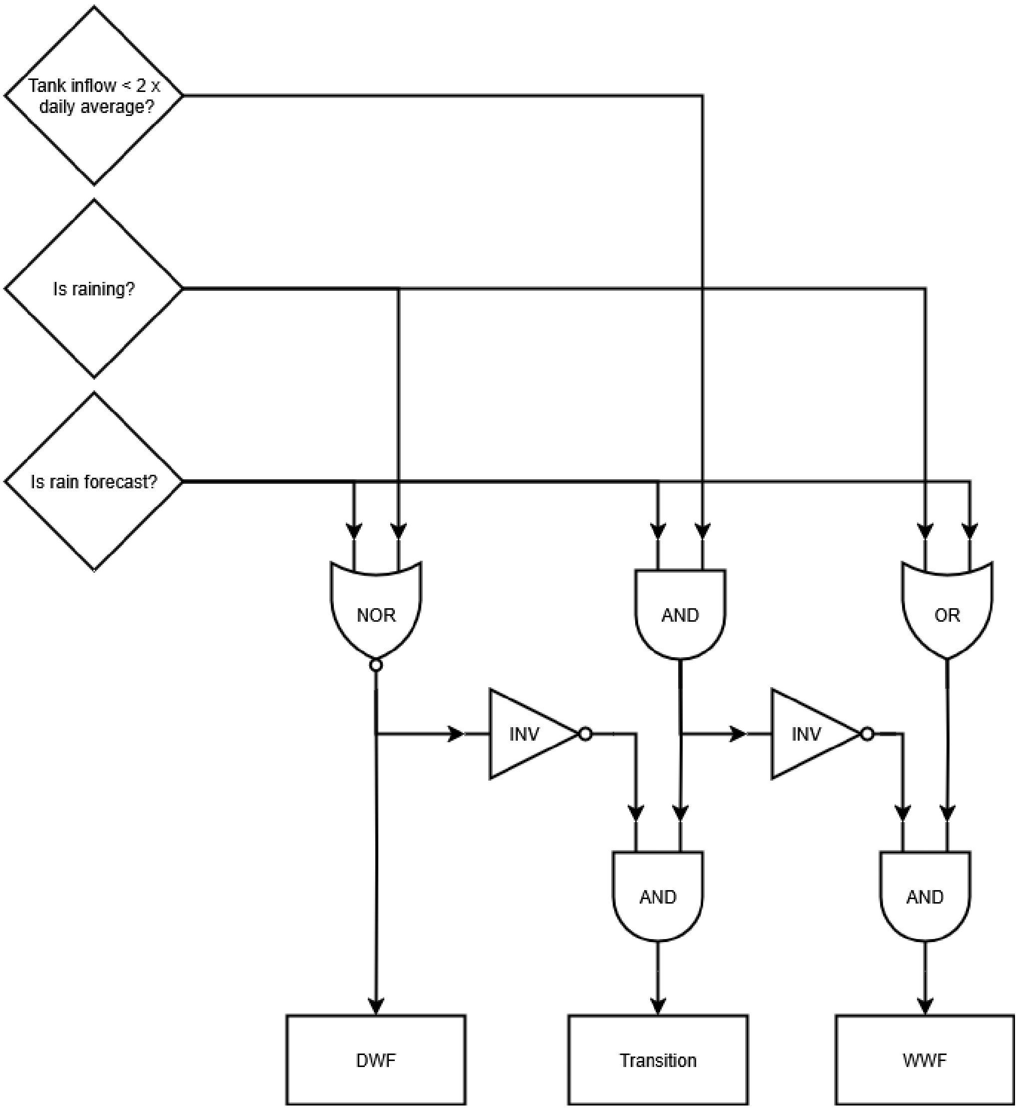


Figure 3.13: Procedure for selecting the various real-time control operational modes (dry weather flow (DWF), wet weather flow (WWF), and a transition phase from dry to wet weather flow (Transition)) based on whether or not it is raining, rain is forecasted, and whether or not the tank inflow is higher than twice the daily average.

As illustrated, the dry weather mode is activated when either no rainfall is observed or forecast. If rainfall is forecast, and inflow to the catchment buffer tank remains below twice the daily dry average–indicating no rain-induced peak flow–then the transition mode is activated. Since rain is forecast, the dry weather mode is no longer active. If rainfall is currently occurring or forecast, and the transitional conditions are no longer met (i.e., inflow exceeds twice the daily dry average), then the wet weather mode is activated. Not depicted in the diagram is a "wet weather linger" state, in which the system remains in wet weather mode until the buffer storage volume falls below 125% of the maximum dry weather storage volume. This mechanism prevents switching back to the dry weather mode before sufficient emptying has occurred.

Logic gates

Figure 3.13 uses several basic logic gates: AND, OR, and INVERTER (INV). The AND gate returns true output only when both of its inputs are true; otherwise, it returns false. The OR gate returns true if at least one of its inputs is true; otherwise, false is returned. The NOR gate returns only returns true whenever both inputs are false. Lastly, the INVERTER (or NOT gate) reverses the input signal, returning false for true and vice versa (Baron et al., 2006).

3.3.4. RTC Operational Modes

With the introduction of the control procedure and determination of which operational mode has to be activated, each individual operational mode can now be elaborated upon. The dry weather flow operational mode is the basis for this thesis, where the catchment outflow is ideally kept as constant as possible to achieve the most significant improvement in operational objective functions 1 and 3. The transition operational mode is the trickiest mode, as it is highly dependent on system state and the resulting analysis from Section 3.2.2. This mode pre-emptively discharges the buffered wastewater when storm events are forecast to provide sufficient stormwater storage capacity. Operational objective functions 2 and 4 are most affected by this mode. Lastly, the wet weather flow mode should best mimic original system behaviour by mimicking exit pumps' flows using the stored pump curves, rather than a maximum flow rate, which was implemented in Section 3.1.1. This mode will only affect operational objective function 4.

Dry Weather Flow

During dry weather conditions, the exit pumps are operated at their ideal outflow flow rate, introduced in Section 3.2.2 as the mean daily dry weather flow. The pump target setting is determined by dividing this ideal flow rate by the pump's maximum capacity. To avoid gradual accumulation in the catchment storage units during extended dry periods, a corrective multiplier is applied to the target setting whenever the storage volume exceeds a predefined threshold: the maximum dry weather buffer volume. The pump target setting is thus computed as:

$$TS_{\text{dry}} = \frac{Q_{\text{ideal}}}{Q_{\text{max}}} \cdot \max\left(\frac{V_{\text{current}}}{V_{\text{DWF,max}}}, 1\right) \tag{3.23}$$

Where:

- TS_{dry}: Target setting of the pump during dry weather conditions [–]
- Q_{ideal}: Ideal flow rate for dry weather outflow $[\mathrm{L}^3/\mathrm{T}]$
- Q_{max}: Maximum capacity of the pump $[\mathrm{L}^3/\mathrm{T}]$
- V_{current}: Current stored volume in the buffer $[\mathrm{L}^3]$
- $V_{\text{DWF,max}}$: Maximum allowable dry weather storage volume $[\mathrm{L}^3]$

Transition Phase from Dry to Wet Weather

During the transition scenario, the pump flow is gradually increased, starting from the ideal flow rate, to empty the buffered dry weather volume to make room for stormwater in the storage unit. The algorithm determines the pump's target setting in the following steps:

1. Compute the *potential target setting* TS_{pot} by taking the maximum of the current inflow Q_{in} and the ideal flow Q_{ideal}, and dividing this value by the pump's maximum capacity Q_{max} (Equation 3.24).
2. Compare TS_{pot} with the previous target setting TS_{prev}. If the difference exceeds 2.5%, the new target setting is increased by exactly 2.5% from TS_{prev}. Otherwise, TS_{pot} is used as the new target setting (Equation 3.24).

$$TS_{pot} = \frac{max(Qin, Qideal)}{Qmax} \tag{3.24}$$

$$TS_{\text{transition}} = \begin{cases} TS_{prev} * 1.025 & \text{if } \frac{TS_{pot}}{TS_{prev}} > 1.025 \\ TS_{pot} & \text{otherwise} \end{cases} \tag{3.25}$$

Where:

- $TS_{transition}$: New target setting in the transition scenario [-]
- TS_{pot}: Potential target setting [-]
- TS_{prev}: Target setting from the previous time step [-]
- Q_{in}: Current inflow into the buffer storage $[\mathrm{L}^3/\mathrm{T}]$
- Q_{ideal}: Ideal dry weather flow $[\mathrm{L}^3/\mathrm{T}]$
- Q_{max}: Maximum capacity of the pump $[\mathrm{L}^3/\mathrm{T}]$

Wet Weather

In the wet weather mode, the pumps revert back to their pump curves if the target flow exceeds the ideal flow; otherwise, the ideal outflow level is maintained. Pump curves are normally implemented as continuous functions across upstream water depth in UDS modelling software; however, pump curves are usually stored in steps. Therefore, an interpolation function is created for each pump, based on the available flow-depth relationship, allowing the target flow to be calculated for any storage depth (Equation 3.26). This target flow is then used to determine the pump's target setting by dividing it by the pump's maximum flow capacity (Equation 3.27).

$$TS_{\text{curve}} = \frac{Q_{\text{curve}}(h)}{Q_{\text{max}}} \tag{3.26}$$

$$TS_{\text{wet}} = \begin{cases} \frac{Q_{\text{ideal}}}{Q_{\text{max}}}, & \text{if } TS_{\text{curve}} < TS_{\text{ideal}} \\ TS_{\text{curve}}, & \text{otherwise} \end{cases} \tag{3.27}$$

Where:

- TS_{curve}: Target setting based on the pump curve [-]
- TS_{wet}: Final pump target setting for wet weather operation [-]
- TS_{ideal}: Target setting for the ideal constant outflow [-]
- $Q_{\text{curve}}(h)$: Interpolated pump flow rate at depth h $[\mathrm{L}^3/\mathrm{T}]$
- h: Storage depth in the buffer $[\mathrm{L}]$
- Q_{ideal}: Ideal flow during dry weather conditions $[\mathrm{L}^3/\mathrm{T}]$
- Q_{max}: Maximum capacity of the pump $[\mathrm{L}^3/\mathrm{T}]$

3.4. Applying Realistic Weather Forecasts

Having implemented the RTC logic using the historic precipitation data as forecast data, the procedure is always able to make the correct choice whether or not to switch to the transitional operational mode or to remain in the DWF mode. While this likely provides better results based on the operational objective functions, it is not realistic. Therefore, the ensemble forecast dataset is used to provide a realistic and practically viable version of the RTC script.

3.4.1. Required Script Adjustments

The RTC logic introduced in Chapter 3.3 is extended to incorporate decision-making based on ensemble weather forecasts. The only adjustments needed are the implementation of a second version of the 'is rain forecast' decision stage and the introduction of two additional parameters: a secondary, catchment-specific rainfall threshold and a catchment-specific confidence level. To identify the optimal rainfall threshold and confidence parameters, an extensive iterative simulation is conducted across a range of possible values for each exit pump attached catchment. For every catchment, all combinations of threshold and confidence levels are evaluated using the RTC with the ensembles script. The objective functions introduced in Section 3.3.2 guide the selection process, primarily the combined objective function, enabling an informed decision on the best rainfall threshold and confidence level for each catchment.

3.4.2. Renewed Forecast Decision Making

Even though the ensemble forecast dataset is only published at 6-hour intervals, precipitation forecasts are evaluated hourly at each simulation step for a specified time window. This window typically spans the 0-6 hours ahead for the short-term forecast check, or the 6 up to 12 hours ahead in case of the long-term forecast check. For each region (e.g., assigned rain gauge in SWMM) and each forecast time step within the window, the 50 ensemble forecast values $x_{(n)}$ are sorted in ascending order:

$$x_{(1)} \leq x_{(2)} \leq \cdots \leq x_{(50)} \tag{3.28}$$

These values form an empirical cumulative distribution, where each value is assigned a quantile rank, evenly spaced between 0 and 1:

$$q_i = \frac{i-1}{n-1}, \quad \text{for } i = 1, \ldots, n, \quad n = 50 \tag{3.29}$$

An interpolation function $F^{-1}(q)$ is created using these quantile ranks q_i as x-values and sorted ensemble values $x_{(i)}$ as y-values:

$$\hat{F}^{-1}(q) = \text{Interpolated value such that } \hat{F}^{-1}(q_i) = x_{(i)} \tag{3.30}$$

This effectively defines a quantile (inverse cumulative distribution function) function, which estimates the rainfall amount that corresponds to a given level of confidence (with q-level confidence, it can be said there will be less than x-level precipitation). For each forecast time step within the window, rainfall is extracted from this interpolation using a region-specific confidence threshold q_c:

$$P_t = \hat{F}^{-1}(q_c) \tag{3.31}$$

The resulting precipitation forecasts P_t for each time step are then averaged over the entire forecast window:

$$\bar{P}_{\text{region}} = \frac{1}{N_t} \sum_{t=1}^{N_t} p_t \tag{3.32}$$

In case of Eindhoven, if the calculated average precipitation, within the forecast window, exceeds the region-specific precipitation threshold, then precipitation is forecast for the Eindhoven region. Each of the Riool Zuid regions is checked in exactly the same manner as described in Equations 3.20, 3.21, and 3.22.

4 Results

This chapter presents the results obtained during this thesis project. It begins by analysing the created models and used data, where specifically the created urban drainage model and water quality model are verified, as well as the precipitation (forecast) data. Next, the results related to the first research question are presented, where the needed time to discharge all stored wastewater and the system's RTC potential are shown. This is followed by an analysis of the performance of the RTC logic by presenting the operational objective functions during the extended summer period and during a period of either dry or wet weather. Lastly, the performance gain in pollutant level is analysed by using the operational objective function score for the same 3 periods.

4.1. Model & Data Analysis

Reliable models and data are key when making any model-based analysis. For this reason, the re-developed urban drainage system in SWMM and the water quality model in Python are extensively verified and tweaked based on a comparison with the original models previously created in WEST. Understanding how and why certain inaccuracies exist and how this impacts later results is important for result interpretation. The precipitation (forecast) data are analysed for completeness and how the ensemble forecast relates to the historical precipitation data.

4.1.1. Urban Drainage Model

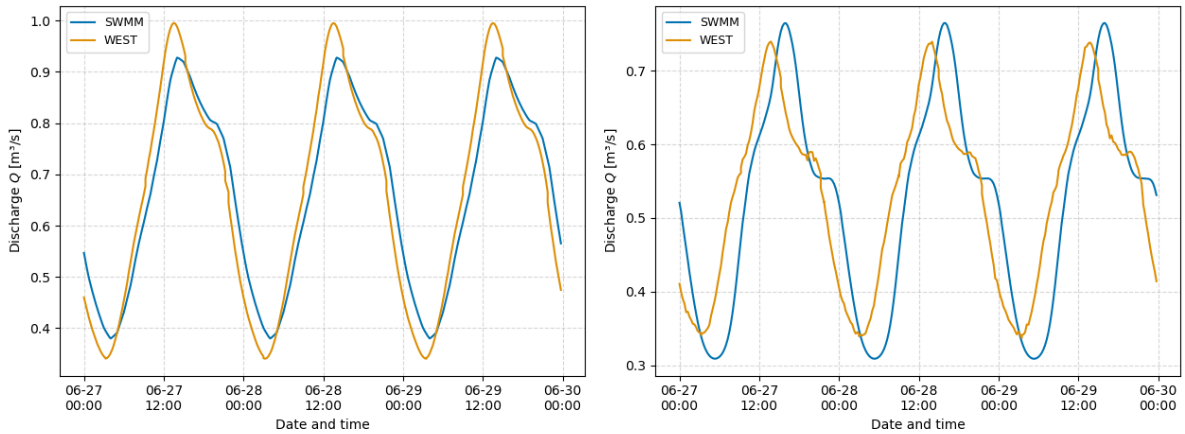
To begin, results comparing the re-created UDS in SWWM with the original WEST model for the extended summer period are presented (Table 4.1). Notably, the Eindhoven catchment was replicated more accurately in terms of NSE, despite Riool Zuid showing a lower RMSE. To clarify this contrast, model performance is further evaluated under dry and wet weather flows.

Table 4.1: Storm Water Management Model (SWMM) model performance, per catchment, as determined by the Nash-Sutcliffe Efficiency (NSE), and the Root Mean Squared Error (RMSE)

Catchment	NSE	RMSE [m^3/s]
Eindhoven	0.76	0.53
Riool Zuid	0.74	0.44

Dry Weather Flow

With the focus of this project being the control of dry weather flow, accurately replicating this flow is essential, as the dry weather flow is directly influenced by the implemented heuristic control rules. Since no outside influences are present here, and flow is generated based on a perfectly repeated steady pattern, meaning no day-to-day variation in generated dry weather flow. Such steady dry weather flow for a dry period is used to compare the exact differences between the SWMM and WEST models (Figure 4.1).



(a) Eindhoven catchment
NSE=0.910, RMSE=0.063 m^3/s

(b) Riool Zuid catchment
NSE=0.531, RMSE=0.084 m^3/s

Figure 4.1: Catchment outflow comparison between SWMM and WEST model per catchment during a dry period

The Eindhoven catchment shows a strong correlation between the SWMM and WEST models in flow pattern, timing, and magnitude, with an NSE of 0.91. Despite a slight underestimation of peak and valley flows in SWMM, the total outflow differs by less than 1%. This strong correlation is caused by the relatively simple implementation of the Eindhoven catchment in WEST, leading to an almost one-to-one copy in SWMM. In contrast, Riool Zuid displays a weaker correlation, with an NSE of 0.53 and a 33% higher RMSE relative to Eindhoven. In WEST the Riool Zuid catchment was implemented in a more complex manner compared to Eindhoven: it combined multiple urban areas, longer travel routes, many different storage buckets, and pumps. This complexity was also reflected in the SWMM model, in addition to the fully hydrodynamic transport pipe. Visual inspection reveals a consistent time lag in SWMM outflow. This was introduced by the section of transport pipe added to the final SWMM model–8.9 km long and absent in the WEST model–introducing a delay of approximately 2.5 hours based on an assumed flow velocity of 1 m/s. Applying this timeshift improves the NSE to 0.95 and reduces the RMSE by two-thirds, confirming that the addition of the transport pipe in the SWMM model as the primary source of model deviation (Figure 4.2).

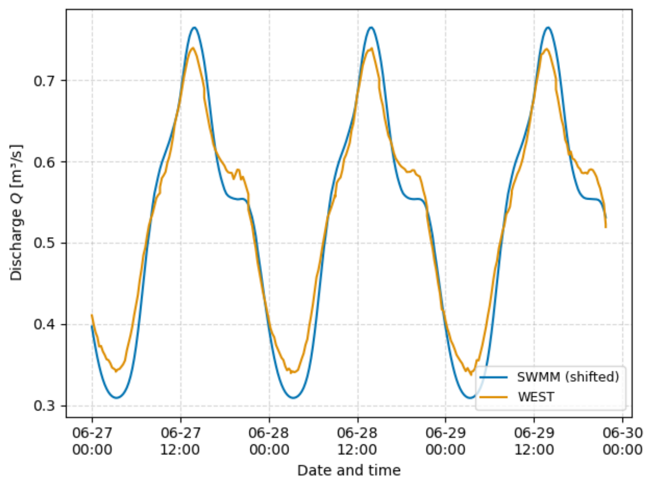


Figure 4.2: Riool Zuid catchment outflow where the SWMM model is shifted backwards in time by 2.5 hours

Both Eindhoven and Riool Zuid (after applying the time shift) show strong agreement with the WEST model under dry weather flow, which is the primary focus of this study. The time shift is not carried forward due to implementation challenges related to water quality estimations. This decision has limited impact, as the catchment outflows have been shown to align well with the WEST model.

The only drawback is a potential shift in the timing of peak outflow loads from this catchment, which could amplify or attenuate WWTP influent peaks. However, since the model results are used and compared in isolation–compared only against other simulation results from the same model–these imperfections do not affect overall conclusions.

Wet Weather Flow

Even though dry weather flow is the primary focus due to its relevance to the implemented heuristic control strategy, it is also important that wet weather outflows are representative. This is because the RTC can significantly affect storage availability, which affects CSO frequency and magnitude, and the transition between dry and wet conditions. As individual sub-catchment flow dynamics are less important, the model's validity under wet weather is evaluated by the exit pump flows, which reflect the entire catchment's behaviour, and is directly related to the control logic. Model accuracy decreased under WWF conditions for both catchments. For the Eindhoven catchment, an NSE of 0.857 and RMSE of 0.576 m^3/s indicate a reasonably strong match between SWMM and WEST during storm events. In the Riool Zuid catchment, when applying the 2.5-hour time shift, the NSE was reduced to 0.775, with an RMSE of 0.583 m^3/s, showcasing a similarly good model behaviour. These reductions in model accuracy compared to the dry weather can be largely attributed to fundamental differences in catchment representation. SWMM employs detailed runoff algorithms with parameters that were roughly estimated, as they could not be directly transferred from the WEST model. Conversely, WEST uses simplified, custom-built (sub-)catchments connected to reservoirs with individual storage and pump capacity. Additionally, in Riool Zuid, the inclusion of the transport pipe and pump flow curves introduced differences in flow compared to the WEST model, where the pump curves have a visible strong effect during peak flows (Appendix Figure B.2). Despite these differences, total simulated outflow remained close, with a difference of 6% for Eindhoven and 4.2% for Riool Zuid. Although wet weather flow accuracy is slightly lower due to model differences, key flow patterns and total volumes remain well represented. This level of correlation is sufficient for the model's intended use in RTC evaluations and is therefore deemed suitable for simulating wet weather conditions in this study.

Combined Sewer Overflow

Since wet weather flow dynamics directly influence CSO frequency and volume, verifying that the model replicates these flows was crucial. To later be able to confirm that the implemented control rules do not increase CSO occurrences, it was essential to verify that the SWMM model accurately replicates CSO behaviour from the WEST model. Maintaining the CSO frequency is critical to avoid worsening existing surface water conditions. For a more detailed analysis, the Riool Zuid catchment CSOs were subdivided into three subsystems: Geldrop, Mierlo, and the combined catchment upstream of the Aalst pumping station (Table 4.2). Both the Geldrop and Eindhoven catchments show an accurate match in CSO frequency during the evaluated period. A slight difference in tank filling degree led to one extra CSO event in Mierlo, with a low average flow of 3.36 m^3/h lasting about 1.5 hours–highlighting how small differences can affect CSO frequency. The larger difference upstream of the Aalst pumping station is primarily due to the catchment of Valkenswaard, where more complex model infrastructure was used in WEST–including multiple controls and a feedback loop–which was simplified in SWMM.

Table 4.2: Number of combined sewer overflows per (sub)catchment over extended summer period (15 March - 15 October)

Catchment	SWMM	WEST
Eindhoven	9	9
Geldrop	11	11
Mierlo	4	3
Upstream of Aalst pumping station	17	25

Previously, this discrepancy between SWMM and WEST CSO events was larger because multiple storage units and CSOs were aggregated into a single storage unit and a CSO, respectively, which was an oversimplification that reduced model agreement. Introducing individual CSOs per sub-catchment (as detailed in Section 3.1.1) helped reduce this gap by providing better model representation. Specifically for the Valkenswaard catchment, 3 storage units and 3 CSOs were added in parallel to better reflect the WEST model.

However, a relatively high number of differences in the number of CSO events in Valkenswaard remained. These differences tend to have a specific set of characteristics:

- During small to medium storm events with a mean precipitation rate of +/- 0.5 mm/hour, or total precipitation of 3 - 7 mm
- Small CSO volume with less than 2 500 m^3 in general per CSO event
- Often as a result of multiple storm events across 20+ hours

With these characteristics in mind, no further adjustments were made to the SWMM model, since these additional and unaccounted for CSOs are caused by a small number of storm events, with little total CSO volume, and primarily because these overflows will experience negligible effects of the implemented RTC. To iterate on the last point, the implemented control rules mainly affect flows downstream, near the exit pump, and do not impact CSO events this far upstream, behind another–unaffected by RTC–pumping station (Aalst). Meaning that, when implementing the RTC, no effects are expected on the number or total volume of CSOs this far upstream at Valkenswaard. The main consequence of keeping these additional CSOs compared to the WEST model is a slightly reduced total inflow to the WWTP during storm events. However, since only the SWMM model will be compared against itself and CSO levels at Valkenswaard across all different scenarios (with equal precipitation rates) will remain constant, this does not affect the results.

4.1.2. Water Quality Model

To accurately determine pollutant levels in the sewer system and their mixing behaviours due to buffering, a representative and accurate water quality model is essential. Additionally, for validating the re-created water quality model, inflow and tank filling degree data were extracted directly from the reference model in WEST as input to the recreated model. This enables an exact replication of effluent pollutant levels if the model is correctly rewritten in Python. Dry weather flow remains the focus, as it is critical for analysing the WWTP effluent effects of the implemented RTC rules. During dry weather conditions, the recreated model achieved a coefficient of determination (R^2) above 0.99 for all six pollutants in both catchments (Appendix Figure B.3), indicating near-perfect replication of the original model in WEST. When evaluated over the full simulation period–including storm events–the model accuracy remained high for most pollutants, but dropped notably for particulate COD and TSS (Table 4.3). This deviation observed in specifically these two parameters is because they are influenced by different internal processes in the water quality model compared to the others.

Table 4.3: Recreated water quality model performance, per catchment, as determined by coefficient of determination (R^2) over the extended summer period

Pollutant	Eindhoven	Riool-Zuid
Particulate COD	0.45	0.31
Dissolved COD	0.94	0.94
NH_4	0.94	0.94
PO_4	0.94	0.94
TSS	0.83	0.82

Considering that no errors were found in the new model Python script, a possible explanation lies in the fundamental difference between the scripting languages: the original declarative mSL versus the sequential Python implementation, where instruction order may influence outcomes. This hypothesis could not be tested within the scope of this thesis. Since NO_4 and PO_4–the key focus of this research–remain unaffected and highly accurate, the lower performance of particulate COD and TSS is not considered problematic. While particulate COD can influence downstream pollutant dynamics, its deviations were not significant enough to significantly impact results, as particularly during storm events deviations occur in particulate COD load (Figure 4.3).

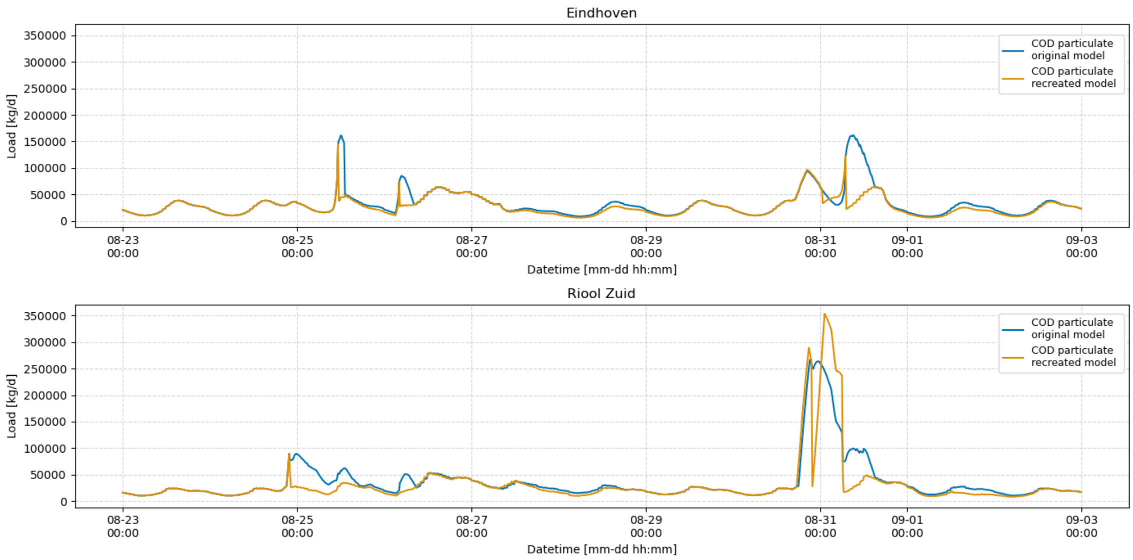


Figure 4.3: Difference in original and recreated water model during storm events for particulate chemical oxygen demand (COD)

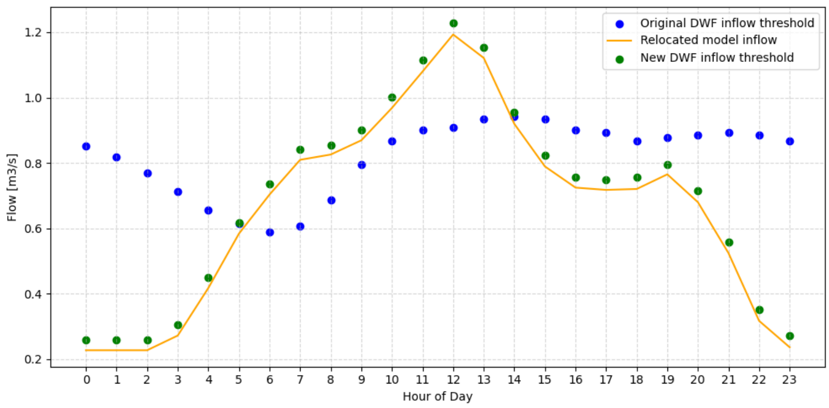
Due to the effects of the implemented RTC, DWF is temporarily stored in the catchment's main storage unit, transforming this storage into a continuously mixed reactor. This mixing alters the timing and concentration of pollutants in the outflow of the catchment, which breaks the original assumption used in the WEST model that inflow at time t equals the outflow at time t during dry weather. As a result, the water quality model had to be repositioned upstream of the buffer to accurately represent the pollutant loads and avoid disruption caused by the dynamics of buffering.

Location Change Inflow Threshold Impact

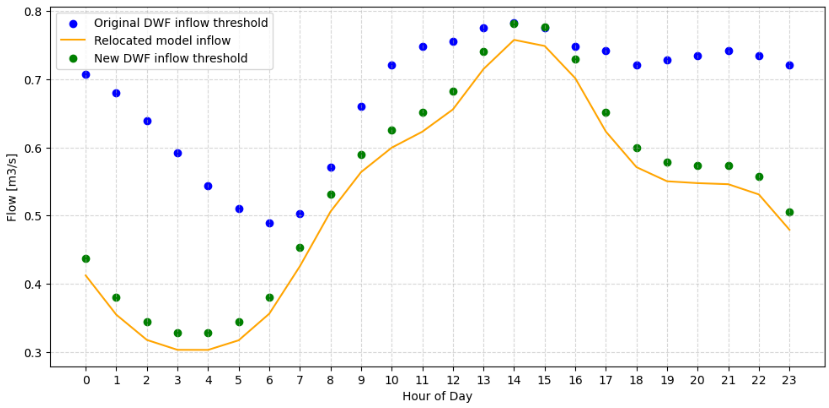
Relocating the water quality model upstream of the storage buffer significantly altered the inflow dynamics, leading to incorrect event-state classification, particularly for logic dependent on flow thresholds. Originally, the model relied on a predefined inflow pattern based on the average 95th percentile flow, with a characteristic hourly distribution of flow. These values reflected the flow conditions into the water quality model after passing through the storage and a pipe section, as modelled in WEST. With the model now positioned before these components, the damping and delay effects, because of the storage and pipe sections, are no longer present. This resulted in a much more variable and sharp inflow pattern. Furthermore, to adapt to the changed inflow pattern, a new predefined inflow pattern was created slightly above the observed inflow curve of the relocated water quality model, ensuring that the event-state logic remained accurate (Figure 4.4). The comparison shows that in both catchments, the original expected flow patterns (blue dots) displayed a narrower range and later peaks compared to the observed inflow at the relocated water quality model (orange line). This difference was particularly impactful in Eindhoven, where the new dry weather inflow exceeded the original dry weather flow thresholds between 05:00 and 14:00. For this reason, the system incorrectly classified these dry weather periods as storm events. To resolve this, an updated DWF flow pattern (green dots) was introduced, positioned above the observed dry weather inflow of the repositioned water quality model.

Pollutant Mixing due to Water Quality Model Relocation

Another consequence of relocating the water quality model is its impact on pollutant loads at the catchment outflows. Since pollutant loads are now calculated upstream of the main storage units, the persistent volume of water in these–present even without RTC–introduces mixing and attenuation effects. This leads to dampened pollutant load and concentration fluctuations at the outflow (Figure 4.5). This improves the model's realism, as the storage behaves like a continuously mixed reactor, smoothing out concentration peaks caused by the diurnal variation. Moreover, similar, but smaller effects were observed in Riool Zuid (Appendix Figure B.4). The smaller effect is caused by the smaller storage volume, with less persistent volume of water always being present at the downstream end of the transport



(a) Eindhoven catchment



(b) Riool Zuid catchment

Figure 4.4: Effects of the change in location of water quality model on the inflow pattern into the model, related to the expected inflow levels during dry weather per hour

pipe. With less volume present, less mixing can occur, since there is not as much capacity to attenuate peaks and inflow becomes more dominant in determining concentration levels in the storage.

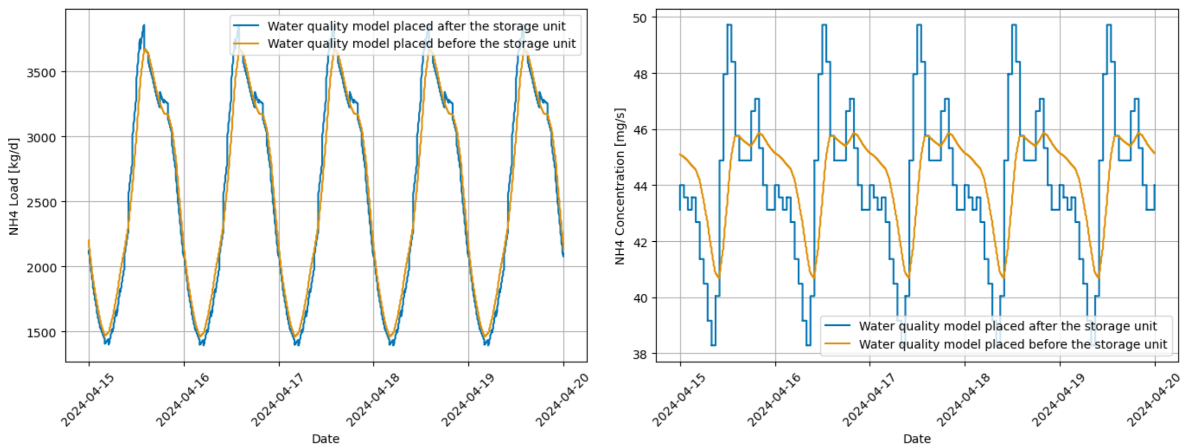


Figure 4.5: Difference in NH_4 load and concentration at the effluent point of the Eindhoven catchment (SWMM), when placing the water quality model before or after the storage unit that summarises the Eindhoven catchment

With the change in water quality model location, and adjustment of dry weather flow threshold, the models were deemed sufficiently accurate to move forward with the implementation of RTC, and testing the resulting effects on WWTP influent, effluent, and surface water quality.

4.1.3. Precipitation (Forecast) Data

This thesis compares RTC performances using both historical precipitation data (as ideal forecasts) and ensemble forecasts. Understanding the differences between these datasets is crucial to assessing their respective strengths and limitations. The analysis is two-fold: first, it establishes an overall understanding of differences between the observed precipitation and the ensemble forecasts; second, it investigates how both datasets differ in forecasting storm events throughout the extended summer period.

To gain an overall understanding of the relationship between the forecasted and actual precipitation, a randomly selected period containing one or more storm events was visualised. It is illustrated how forecasts for the subsequent 58 hours–generated at time t and depicted using boxplots–compare to the actual recorded precipitation (Figure 4.6). Several observations can be made from the figure. First, although the forecasts are created at 18:00, the available ensemble forecasts from this timestamp are only two hours later. While this delay does not pose a direct issue for the weather forecast analysis, it was necessary to account for this by shifting the forecast evaluation window forward by two hours–changing it from 0-6 hours ahead to 2-8 hours ahead (and from 6-12 hours to 8-14 hours ahead). Secondly, while the forecasts showed limited accuracy in terms of predicted precipitation quantity, they were able to qualitatively identify the timing of two larger storm events across both days.

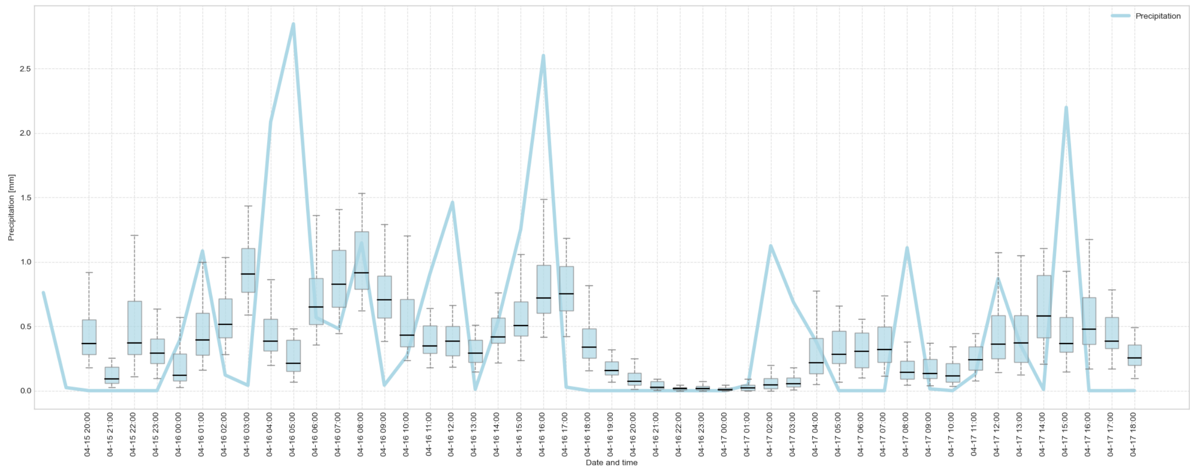


Figure 4.6: Precipitation over a period (solid light blue line), plotted against the forecast ensembles created at 18:00, represented by the boxplots

The ability for the ensemble dataset to predict storm events is related to the forecasts using the historical dataset over the extended summer period (Tables 4.4 & 4.5). The used rainfall threshold and confidence parameters for the ensemble forecast analysis are based on the results described in Section 4.3.1 (Table 4.9). In Riool Zuid specifically, nearly all storm events were correctly detected, both at the hourly and event levels, demonstrating high sensitivity. On the other hand, Eindhoven showed a more balanced performance, with fewer missed events but also fewer false positives. Across both locations, a relatively high number of false positives suggests that dry periods were often misclassified as wet, which leads to unnecessary system responses. The high number of false positives indicates that the confidence level used is low. Such a relatively low confidence level, leading to more false positives, makes the system more conservative, and executing more frequently the pre-emptive draining behaviour. While this is generally unwanted, it is preferred over having more false negatives, which could lead to an increase in CSO severity and frequency. Overall, the ensemble dataset proved capable of reliably identifying upcoming storm events, and to a lesser extent, dry periods, especially when evaluated on an event basis. It highlights the ensemble forecast data's strength as an early warning tool, even if precision remains an area for improvement.

Table 4.4: Confusion matrix describing the forecasting performance of the ensemble dataset with respect to the perfect forecasts using the historical precipitation dataset. This table shows the forecast performance per hour, where correct forecasts are highlighted in bold, false positives in italic, and false negatives are underlined.

	Eindhoven		Riool Zuid	
	Ensemble positive	Ensemble negative	Ensemble positive	Ensemble negative
Perfect positive	**213**	<u>111</u>	**1075**	<u>2</u>
Perfect negative	*279*	**3729**	*1378*	**1877**

Table 4.5: Confusion matrix describing the forecasting performance of the ensemble dataset with respect to the perfect forecasts using the historical precipitation dataset. This table shows the forecast performance per storm event (based on the historical precipitation dataset), where correct forecasts are highlighted in bold, false positives in italic, and false negatives are underlined.

	Eindhoven		Riool Zuid	
	Ensemble positive	Ensemble negative	Ensemble positive	Ensemble negative
Perfect positive	**20**	<u>6</u>	**49**	<u>0</u>
Perfect negative	*22*	**43**	*43*	**91**

4.2. Wastewater System Characteristics and Capacities

With a reliable set of models established, it is essential to understand how these models interact, what their key characteristics are, and how they perform under different conditions. This knowledge forms the basis for designing the RTC logic and its parameters. To do so, an analysis was carried out on how long it takes to empty the system's storage buffers, the current system performance in terms of CSO volume and flow stability, and the effect of the three scenarios on pollutant levels at the WWTP effluent.

4.2.1. Time to Empty

Since the sewer network is used as temporary storage to buffer wastewater to attenuate peak flows, less storage capacity will be available when a storm event occurs to buffer stormwater and prevent overloading the WWTP, CSOs, and surface flooding. Ideally, the stored wastewater is removed from the storage unit when a storm event is forecast. Identifying how fast and how early this needs to be done is essential to avoid overloading the treatment plant. The first step in this is to analyse the theoretical maximum required volume of wastewater that is buffered on a daily basis.

To analyse the theoretical maximum required buffer capacity, the dry weather outflow of the catchments was used as the inflow to a virtual buffer storage. The outflow from this buffer was calculated by taking the mean dry weather flow over the extended summer period. This mean flow represents the ideal outflow levels used as RTC target setting, for Eindhoven this value was 0.663 m^3/s, and for Riool Zuid 0.5218 m^3. This approach generated a storage volume pattern, illustrating how the buffer would be utilised over time under dry weather conditions with ideal outflow levels (Appendix Figure B.5). Under these theoretical dry weather conditions, the Eindhoven catchment reached a maximum stored volume of just over 7000 m^3, while Riool Zuid reached a volume of 5000 m^3/s. In practice, during the later implemented RTC, it showed that the daily maximum was about 1.5 times higher, at 11 000 m^3 for Eindhoven and 7500 m^3 for Riool Zuid. Ground for this was the already persistent available volume of water in both the WEST and SWMM models to prevent an empty storage chamber that could lead to a disabled exit pump, leading to an oscillating outflow pattern that is suboptimal for WWTP operations. The values of 11 000 m^3 for Eindhoven and 7500 m^3 for Riool Zuid are used as maximum allowable dry weather storage volume thresholds, as they are realistically achievable, while not increasing overall buffer volume by a degree that would impose additional risks.

To best analyse the impact of various maximum allowable dry weather storage volumes and the pump rates to empty these volumes, an illustration is made of the time required to empty a given buffered volume at a constant outflow rate (Figure 4.7). The pump rate shown in the figure represents the rate required to fully empty the stored buffer volume within a given time frame, assuming no inflow into the storage. However, since inflow is always present, the actual required pump rate must be in surplus to the inflow to account for both emptying the buffer and the inflow. Consequently, the maximum pump rate depicted in the figure is limited to approximately 0.65 m^3/s, which aligns with the average dry weather flow rate of the Eindhoven catchment. This constraint ensures that the combined pump rate does not exceed the typical maximum daily flow by more than 50% to prevent overloading of the treatment plant.

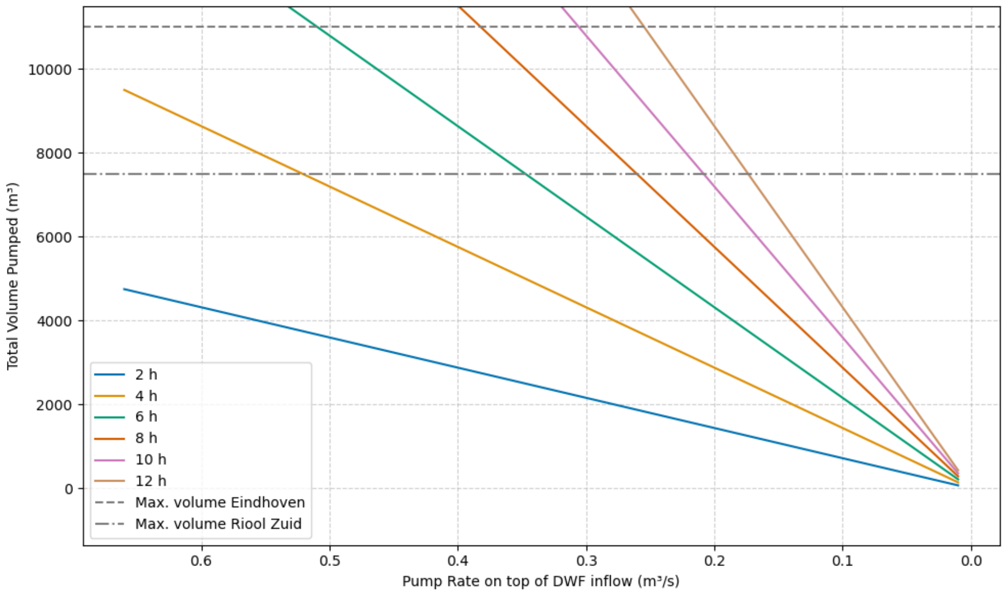


Figure 4.7: Time required to pump a given buffered volume at a set pump rate, representing the additional flow capacity required in addition to the regular dry weather flow.

From the figure, it can be observed that starting the emptying six or fewer hours in advance at lower storage levels–specifically less than half the maximum volume–is sufficient. At higher storage levels, a longer lead time becomes necessary. This extended time frame is particularly important given that sudden, block-wise increases in flow rate are undesirable. For this reason, a second forecast check was implemented, for 6 to 12 hours ahead. Additionally, abrupt changes in pollutant-heavy inflow can place a strain on the WWTP, potentially leading to increased effluent levels. For this reason, the implemented control strategy uses a gradual ramp-up of the pump rate. Although this approach may result in fuller storage tanks at the start of storm events, it is more favourable for the downstream treatment processes.

4.2.2. System Characteristics

The characteristics of the urban drainage system was analysed through three scenarios: (1) a baseline scenario without RTC, including both dry and wet weather flow, to serve as reference for the later RTC results, (2) a scenario with only dry weather flow to compare with scenario (3) a scenario with a constant dry weather flow to evaluate the potential benefits of a constant WWTP influent flow on WWTP effluent quality and river water quality.

Operational Characteristics

The operational characteristics are evaluated over the extended summer period. Two previously introduced operational objective functions–flow variance during dry weather and filling degree at the start of a storm event–are omitted, as they rely on RTC operational modes not present in this stage of analysis. As expected, scenarios 2 and 3 (without storm events) show no combined sewer overflow, while the baseline scenario results in total CSO volumes of 144 m^3 in Eindhoven and 560 m^3 in Riool Zuid (Table 4.6). The constant dry weather flow scenario achieves an ideal flow ratio of 1.0, meaning the target outflow is reached 100% of the time within the 5% margin, as expected from a fixed flow. In contrast, fluctuating daily inflows in the other scenarios yield a much poorer performance–e.g., in Eindhoven's baseline case, the target flow is achieved only $1/15.11 * 100\% = 6.6\%$ of the time. This improves in scenario 2, due to the absence of precipitation leading to more stable inflow conditions.

Table 4.6: Operational objective function values for the three sensitivity scenarios, with CSO representing combined sewer overflow, and DWF standing for dry weather flow

Metric	Scenario	Eindhoven	Riool Zuid
Total CSO volume [m^3]	(1) Baseline	144.01	560.43
	(2) DWF only	**0**	**0**
	(3) Constant DWF	**0**	**0**
Ratio of ideal flow over time with 5% margin	(1) Baseline	15.11	13.75
	(2) DWF only	13.09	9.53
	(3) Constant DWF	**1.00**	**1.00**

Performant Characteristics WWTP Influent

To assess the impact of constant flow on WWTP influent quality, the concentrations of NH_4 and PO_4 are evaluated across the three scenarios over the extended summer period. A clear distinction must be made between the baseline scenario, which includes storm events, and the other two, which only represent dry weather conditions. Stormwater dilutes wastewater, leading to lower pollutant concentrations but higher overall loads. As such, the baseline cannot be directly compared to the dry weather scenarios. The baseline values can, however, later be used as a comparison to the results achieved by the system when using RTC. Average and daily maximum concentrations are consistently lower in the baseline, while pollutant loads are higher (Table 4.7). It is also important to note that the WWTP influent includes contributions from the Nuenen and Son catchments, which are unaffected by changes made and always provide uncontrolled dry and wet weather flow.

Because no treatment has yet occurred, mass balance ensures that both average concentration and load differ by less than 0.8% between DWF-only and constant DWF scenarios. However, the average daily maximum load is significantly reduced–by approximately 26% for NH_4 and PO_4–when using a constant DWF. This reduction in peak pollutant loads represents the most substantial theoretical benefit of applying the RTC logic at the WWTP influent. Loads are now flattened since flows are fully flattened in the constant scenario and any variation in load is caused only by the already attenuated variation in concentration. Additionally, the continuously mixed storage buffer dampens concentration peaks, reducing daily maximum concentrations by around 4% on average for both pollutants in the constant flow scenario.

Table 4.7: Objective function values for the three scenarios applied to the WWTP influent, with the best-performing scenarios per metric highlighted in bold and DWF standing for dry weather flow

Metric	Scenario	NH_4	PO_4
Average concentration [mg/L]	(1) Baseline	39.81	6.42
	(2) DWF only	**44.00**	**7.10**
	(3) Constant DWF	44.33	7.15
Average load [kg/d]	(1) Baseline	5514.89	889.90
	(2) DWF only	4918.12	793.60
	(3) Constant DWF	**4913.00**	**792.77**
Average daily maximum concentration [mg/L]	(1) Baseline	45.04	7.27
	(2) DWF only	47.16	7.61
	(3) Constant DWF	**45.30**	**7.31**
Average daily maximum load [kg/d]	(1) Baseline	7860.71	1268.43
	(2) DWF only	6900.61	1113.51
	(3) Constant DWF	**5058.61**	**816.28**

Performant Characteristics WWTP Effluent

To investigate how changes in WWTP influent conditions affect effluent quality, total nitrogen and total phosphorus are evaluated at the treatment plant effluent (Table 4.8). This analysis provides insight into how the WWTP responds to varying influent dynamics. As with the influent analysis, a clear distinction must be made between the baseline scenario–which includes storm events–and the two dry weather scenarios, making direct comparison inappropriate. Similarly, the contribution from the Nuenen and Son catchments cannot be forgotten.

Interestingly, where previously the levels at the influent of both the average and daily maximum concentration are lower when comparing scenario 1 to scenarios 2 and 3, this is no longer the case at the effluent. Due to the higher hydraulic load during wet weather situations, the retention time in the treatment plant becomes lower, reducing treatment efficiency, leading to effluent with higher pollutant levels. Despite the fact that balance of mass is no longer required for the average load and concentration of total phosphorus, since now the treatment process is present in this balance equation, no change in average concentration and little change in average load (-4%) in the two dry weather scenarios is observed, indicating that during dry weather the treatment plant is sufficiently able to treat phosphorus. In contrast, while total nitrogen remains unchanged in average load, a small change in the average concentration (+1.5%) is observed. This difference is primarily caused by the difference in recirculating flows being added at the influent of the anoxic treatment processes. Where the DWF only scenario has periods of low flow, allowing for better treatment, the scenario with constant flow does not. Because of this, the DWF-only scenario has such significant downward peaks in effluent TN concentration: its average over an entire day is lower (Figure 4.8). The differences in averages of the daily maximum concentration and load, between the two dry weather scenarios, observed at the influent of the treatment plant carried over to the effluent one to one. Where previously a reduction in peak concentrations was observed of about 4% at the influent, the effluent has a reduction of 5.5% for both pollutants. Similarly, the average daily maximum load, reduced by 25% at the influent, is also 25% lower at the effluent. This shows that peak reduction achieved by RTC, due to active buffering of wastewater in the urban drainage network, has a direct impact on peak loads and concentrations entering the receiving surface waters.

Table 4.8: Objective function values for the three scenarios applied to the wastewater treatment plant effluent, with the best-performing scenarios per metric highlighted in bold and DWF standing for dry weather flow

Metric	Scenario	Total Nitrogen	Total Phosphorous
Average concentration [mg/L]	(1) Baseline	5.45	0.44
	(2) DWF only	**5.27**	**0.41**
	(3) Constant DWF	5.35	**0.41**
Average load [kg/d]	(1) Baseline	910.49	80.18
	(2) DWF only	566.02	44.95
	(3) Constant DWF	**564.09**	**43.18**
Average daily maximum concentration [mg/L]	(1) Baseline	6.63	0.54
	(2) DWF only	5.83	0.47
	(3) Constant DWF	**5.49**	**0.44**
Average daily maximum load NH4 [kg/d]	(1) Baseline	1794.88	159.16
	(2) DWF only	959.01	79.81
	(3) Constant DWF	**699.7**	**56.34**

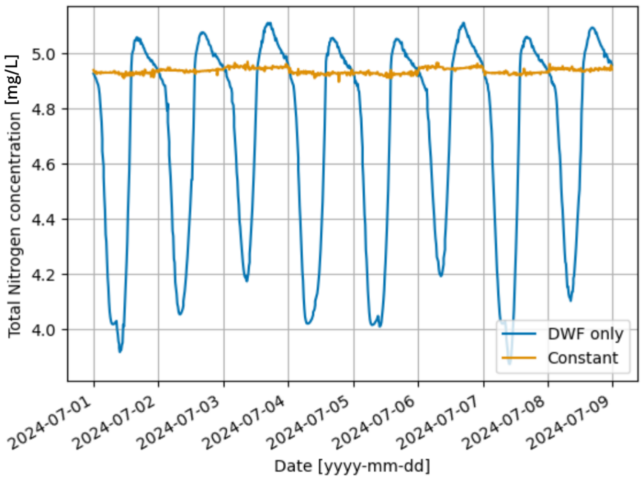


Figure 4.8: Total nitrogen concentration at the effluent, highlighting how the dry weather flow (DWF) only scenario has significant downward peaks, resulting in a lower average concentration

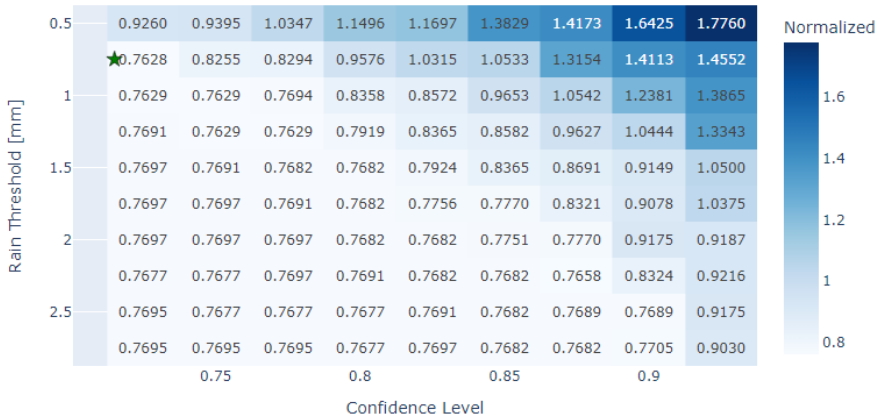
4.3. Operational Real-Time Control

After having (re)created the necessary models, validated them, and analysed the system's base characteristics, control logic was added to the catchment exit pumps to control the outflow of the catchments. This control logic should ensure a more constant flow out of the catchments by using the storage capacity in the sewer network to temporarily buffer wastewater during peak flow hours. The effects of adding this control logic on the operational and performant objective function are discussed next.

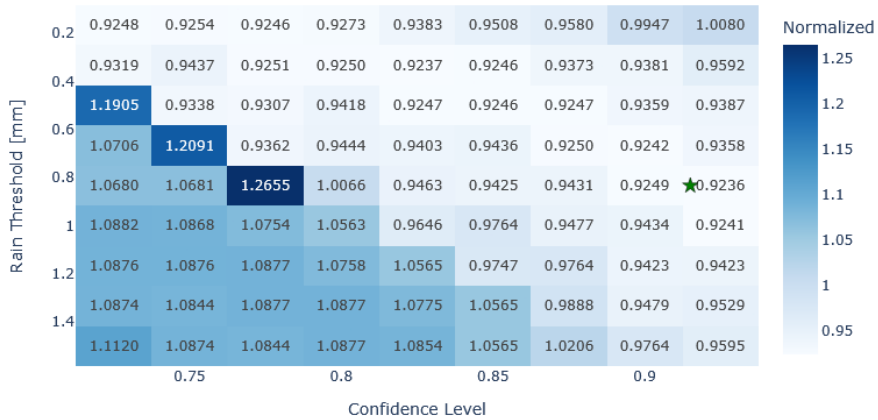
4.3.1. Ensemble Forecast Decision Making Thresholds

To make a more real-world applicable analysis of the impacts of real-time control, ensemble-based weather forecasts, with inherent uncertainty, were added to the decision-making logic. For these forecasts, additional parameters were required for the forecast decision-making process: Therefore, an analysis was performed to identify the optimal parameter combination of precipitation threshold and confidence level. For every possible combination of parameters, a heat map was created of the combined objective function (Section 3.3.2) that shows which combination of parameters performs best for the selected catchment (Figure 4.9).

An interesting contrast between the two catchments was found: Eindhoven performs in general better with lower rain threshold and lower confidence, while Riool Zuid has a bandwidth of particular sets of rain threshold and confidence level that function well. The top-performing parameters are selected per catchment (Table 4.9). These top performing parameters also have contrasting numbers. Whereas Eindhoven has a low confidence level, Riool Zuid has the opposite with much higher confidence level. The difference in confidence level can be attributed to the sensitivity of the used storage capacity at the exit pump to rain flows. This storage capacity in Eindhoven is much larger allowing for less accurate rain forecasts, whereas the downstream storage capacity in Riool Zuid is about 5 times smaller (165 000 vs 35 000 m^3), resulting in a faster filling storage and requiring more sensitive forecasts to prevent CSOs. Interestingly, Riool Zuid displays a diagonal band of good performing metrics, with on the outer edges two sets of worse performing parameter combinations. Based on the analysis of the individual contribution metrics, time series analysis of the pump flow rate, and storage volumes, the following is found: The combination of high confidence level, with low precipitation threshold (top-right), leads to more frequent disengagement of the DWF operational mode. As a result, flow is less often at the ideal constant outflow level, leading to a worse score in terms of flow variance and much lower total time where flow is within 5% of the ideal outflow level. On the other side of the band (bottom-left), flow during the dry weather operational mode is more frequently at the ideal constant level, but displays much higher values in flow variance during dry weather.



(a) Eindhoven catchment



(b) Riool Zuid catchment

Figure 4.9: Combined objective function score (lower is better) for combinations of precipitation threshold and confidence level for ensemble-based forecast decision making, best scoring metric highlighted with green star

Table 4.9: Optimal precipitation threshold and confidence level for ensemble forecast-based decision making

Catchment	Precipitation Threshold [mm]	Confidence Level
Eindhoven City	0.75	0.70
Riool Zuid	0.80	0.925

Interestingly, the best-performing precipitation threshold identified for the ensemble forecast-based decision making is similar to those previously applied in the perfect prediction approach–0.75 mm versus 1 mm for Eindhoven, and 0.8 mm versus 1 mm for Riool Zuid. This suggests that the parameters selected for the perfect prediction scenario were already close to the optimal threshold value.

4.3.2. Overall Flow Performance

An evaluation of the the performance of both RTC implementations and comparing them to the baseline (DWF and WWF) with respect to flow flattening, tank filling degree, and overall RTC behaviour was performed (Table 4.10). The following stands out: Despite buffering wastewater, the total CSO volume in the Eindhoven catchment has been reduced. This reduction is primarily caused by two factors. Firstly, under regular conditions, the system already maintains a fluctuating base volume of around 10 000 m^3 in the storage–a result of the way the system is modelled in WEST, which carried over to the SWMM model. As a consequence, the total volume present in the system during the dry weather RTC may already be similar or lower, which, in the worst case, only leads to equal CSO levels.

Secondly, the RTC strategy includes a transition phase, during which the stored wastewater is pre-emptively emptied, further reducing the stored volume and thus the likelihood and magnitude of combined sewer overflows. In contrast to Eindhoven, the Riool Zuid catchment shows no change in CSO volume, which can be explained by the difference in catchment layout: While Eindhoven has a single storage tank in its catchment, which is directly connected to the only CSO in the catchment, Riool Zuid has many more storage tanks and CSOs–most of which are far upstream from the primary storage tank on which RTC is applied, reducing the effects on CSO levels.

A significant performance improvement can be observed in terms of flow flatness in both catchments. The 5% margin metric improved from values above 13 to below 2 in both Eindhoven and Riool Zuid. A score of 1.5 corresponds to an ideal outflow maintained within a 5% margin during 66% of the dry and transition time steps, whereas a metric value of 13 only corresponds to roughly 8% of the time. Unlike the ideal constant flow scenario, this value is still subject to small precipitation events and transition periods, making a perfect score of 1 unobtainable. The achieved scores of about 1.5 show that the RTC logic is very well able to control the flow during non-storm event periods, and that the ensemble forecast is overall able to match the performance of the perfect weather predictions. This is especially the case for the Eindhoven catchment, where differences are less than 3% compared to a larger difference of 18% in the Riool Zuid catchment.

Furthermore, flow variance in the Eindhoven catchment remained relatively unchanged between ensemble-based and RTC approaches. However, Riool Zuid shows a more significant change, with an improvement in variance with the ensemble method. This is due to the confidence level in the forecast, resulting in more frequent transition periods and thus a lower average storage level. This lower storage level may then lead to a less frequent activation of the storage threshold DWF multiplier, which increases variance. This highlights an issue in RTC design, where a constant value is used over the entire simulation period, rather than a dynamic, day-to-day based ideal outflow value. The lower average storage level also explains the reduced storage volume at the start of storm events in the ensemble scenario.

Table 4.10: Objective function values for the three scenarios; best-performing scenario per metric are highlighted in bold, with DWF standing for dry weather flow, WWF for wet weather flow, CSO for combined sewer overflow, and RTC for real-time control

Metric	Scenario	Eindhoven	Riool Zuid
Total CSO volume [m^3]	DWF and WWF	144.01	**560.43**
	RTC	**115.05**	**560.43**
	Ensemble	120.34	**560.43**
Ratio of ideal flow over time with 5% margin	DWF and WWF	15.11	13.75
	RTC	**1.40**	**1.52**
	Ensemble	1.44	1.79
Flow variance during DWF	RTC	**0.014**	0.024
	Ensemble	0.016	**0.018**
Filling degree start of storm event	RTC	0.09	0.27
	Ensemble	**0.08**	**0.25**

While the difference in metrics in Eindhoven for the perfect and ensemble forecasts is minimal, a more considerable difference can be observed in Riool Zuid. During dry periods, the ensemble forecast more often predicts an incoming storm event, triggering the transition phase (Figure 4.10). During three distinct periods, the ensemble method forecasts a storm event, leading to a switch of operational mode to the transition mode. These transitions are triggered by an overestimation in the ensemble precipitation forecast for the three individual storm events occurring on June 12th, 13th, and 14th. Due to the more complex nature of Riool Zuid–3 datasets, 3 distinct decisions, and different catchment sizes–accurate forecast analysis and decision making are more complex in this catchment, with the probability of errors in the forecast becoming more likely. Therefore, unnecessary transition phases become more frequent. These transition phases increase the pump flow rate step-by-step to empty the stored wastewater volume. This additional emptying disrupts the balance in stored volume and ideal outflow–where volume is stored during the day to be able to maintain a constant outflow during the night. Consequently, it can occur that the storage volume becomes too empty during daily periods of low flow (e.g., night), which halts the pump flow (Figure 4.10). This causes higher flow variance during dry weather periods, less total time where the system has ideal outflow, but it also may cause less total stored volume (a lower filling degree) at the start of storm events. As a result, the RTC flow has a dry weather flow variance of 0.003, while the ensemble dry weather flow has a variance of 0.01. The total duration of flow flatness was also reduced from $1/1.12 = 89\%$ of time to only $1/1.92 = 52\%$ in the ensemble controlled flow. In this example, due to the timing of the actual storm event, no difference is present between the filling degree at the start of the storm event.

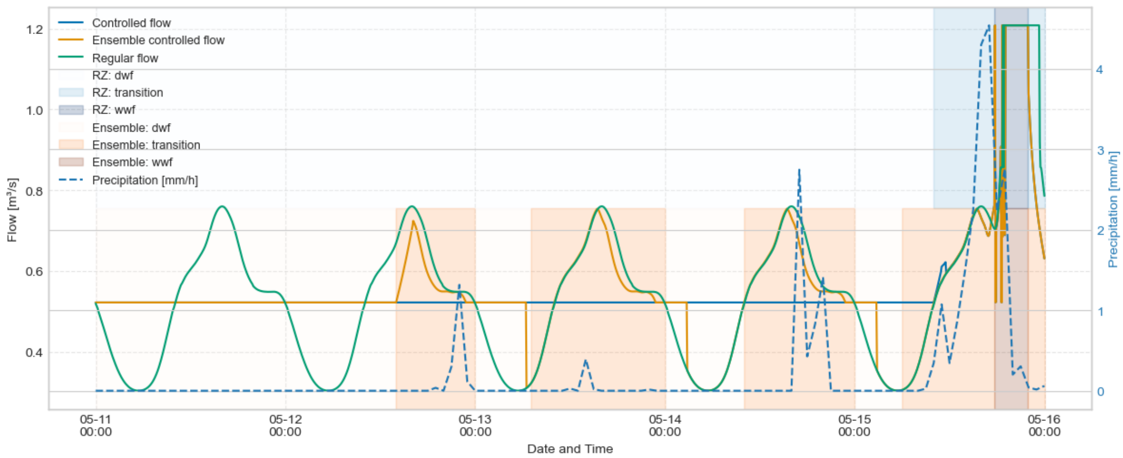


Figure 4.10: Riool Zuid outflow zoomed in on problematic period for the Ensemble RTC method. The various operational modes, per catchment (Eindhoven on top, Riool Zuid on the bottom), are presented as coloured boxes. Additionally, the actual precipitation over the 3 Riool Zuid catchments is added

4.4. Performant Real-Time Control

After having gained insight into the flow-based performance of the implemented RTC logic, a transition can be made to evaluate the effects on water quality metrics. This transition specifically analyses how the WWTP's influent and effluent conditions have changed due to the implemented logic over the extended summer period, a period of dry-only flow, and a period including a storm event. Moreover, a comparison is made to the previously established baseline (scenario 1 in Section 4.2.2), to see what the exact effects of the implemented control logic were. In addition, it is evaluated if the observed changes in the influent and effluent between the dry weather flow only scenario and the constant dry weather flow scenario (scenarios 2 and 3 in Section 4.2.2) are also visible when comparing scenario 1 to the changes in pollutant due to the RTC logic.

4.4.1. Performance at Influent

Analysing the objective function gain in influent characteristics over the extended summer period shows that the average concentration and load experienced only marginal differences between the baseline and the two controlled scenarios (Appendix Table C.4). This corresponds to the observed changes in the comparison between the dry weather flow only and the constant dry weather flow scenario. Additionally, when comparing the metrics between the two pollutants, a strong similarity is observed. Since the pollutants have not experienced any outside influences that would cause differences between the pollutants, differences created by the implemented control logic are carried over one-to-one between the pollutants and are therefore consolidated to a single metric. The two RTC scenarios reduce the average concentrations by just 1.5%, and average load by 0.1% when compared to the baseline uncontrolled scenario. Pollutants in the baseline scenario do not enter the continuously mixed reactor, but instead are straight passed on to the outflow of the reactor. This was handled in such a way as to fit the pollutant pattern better to the observed diurnal pollutant pattern at the outflow of the catchments. However, as shown by the difference in the average concentration, this does cause some inconsistency. Moreover, both pollutants saw a reduction of average daily maximum concentration by 6.7%, and average daily maximum load of 8.6% when using perfect weather forecasts, and a reduction of 5.9% when using ensemble forecasts, monitored over the extended summer period.

During a period of only dry weather, and during a period including a storm event, stronger differences occur (Table 4.11). What stands out in these metrics is that in both dry and wet weather, the RTC performs better than the baseline. The strongest effects of the RTC logic are observed in the changes in averages of the daily maxima, just as in Section 4.2.2. Additionally, due to the previously described inconsistency, a relatively large difference can be observed in average load and concentration when comparing the RTC to the baseline. Moreover, the difference in average concentration during the evaluated storm event is even larger. This is attributed to the pre-emptive emptying of the storage, ensuring most of the stored wastewater is already sent to the treatment plant before a storm event starts. In the baseline scenario, without any RTC, the catchment storage unit still contains a considerable volume of wastewater as mentioned in Section 4.2.1, which gets pushed onto the WWTP together with storm water, leading to higher concentration levels.

Table 4.11: Relative difference in objective function, when compared to the baseline, in a dry period and a wet period at the wastewater treatment plant influent. Differences between NO_4 and PO_4 are negligible and therefore consolidated to a single metric, with RTC meaning real-time control

Metric	**Scenario**	**Dry**	**Wet**
Average concentration [mg/L]	Baseline	44.01	40.26
	RTC	-2.45%	**-5.12%**
	RTC w/ Ensemble	**-2.57%**	-4.84%
Average load [kg/d]	Baseline	4875.74	5290.57
	RTC	-1.85%	**-1.91 %**
	RTC w/ Ensemble	**-2.01%**	-1.2%
Average daily maximum concentration [mg/L]	Baseline	46.74	45.06
	RTC	-6.85%	**-7.75%**
	RTC w/ Ensemble	**-6.97%**	-7.52%
Average daily maximum load [kg/d]	Baseline	6586.19	7880.35
	RTC	-24.7%	-7.98%
	RTC w/ Ensemble	**-25.01%**	**-15.49%**

Additionally, it can be observed that during the dry weather period, the RTC using ensemble forecasts outperforms the RTC approach using perfect forecasts. To better understand this difference, a per-catchment analysis is performed. This allows for a more detailed view of how each catchment contributes to the overall changes in WWTP influent under each scenario, and whether any specific catchment shows notably better performance or behaviour (Appendix Tables C.3 & C.2).

A closer look at the Eindhoven catchment reveals a slight difference in pollutant concentrations between the two RTC approaches, which explains the observed difference in WWTP metrics (Figure 4.11). This difference originates from the catchment's response to a storm event on the 8th of August (not pictured), which caused different stored volume levels and subsequently affected the degree of concentration attenuation at the catchment outflow. These changes result in lower peak concentrations and loads, and small differences in the average values between the two scenarios.

Beyond Eindhoven, a broader pattern is observed, showcasing how both major catchments–Eindhoven and Riool Zuid–shape WWTP influent dynamics. Together, these two catchments contribute over 90% of the average load NH_4 to the treatment plant, with average daily loads of 2766.86 kg/d and 2233.6 kg/d, respectively. This underlines their dominant role compared to the much smaller Nuenen & Son catchment. In both main catchments, the RTC logic leads to clear attenuation of daily load and concentration peaks. However, during dry periods, Eindhoven displays higher average pollutant loads under both RTC scenarios. This difference between catchments is caused by the difference in catchment characteristics (Section 2.1), as Riool Zuid spans a larger area with longer travel times, the flow and concentration are more spread out over the day. In the Eindhoven catchment, two clear concentration peaks can be identified (Figure 4.11 bottom-left), requiring a much larger buffer volume to attenuate these peaks, which the system is unable to do. As the Riool Zuid catchment has a more flat concentration pattern, with only a single peak, the outgoing load is more constant during dry periods, with only small load peaks during the concentration peak (Figure 4.11 top-left). Since both catchments are combined at the WWTP influent, the revelative gains in load and concentration in the Eindhoven catchment are balanced out with the gains in those metrics from the Riool Zuid catchment–leading to an overall more constant WWTP influent. Lastly, the Riool Zuid catchment shows a strong oscillation during the storm event in the outgoing load. Since only the load is affected, and not the concentration level, this hints at an oscillation in flow rate. This is caused by the pump curve–that relates storage water depth to flow rate–used at the outflow point of Riool Zuid, where oscillations in pump rate are caused due to water depth being right around the point between two flow rates (depth around 8.703 and 8.710, vary from 1.2 to 2.5 m^3/s). These results highlight some of the limitations of in-sewer buffering, namely that despite continuous mixing of pollutant concentration over time, the Eindhoven catchment is unable to fully attenuate the daily concentration peaks due to a lack of buffered volume.

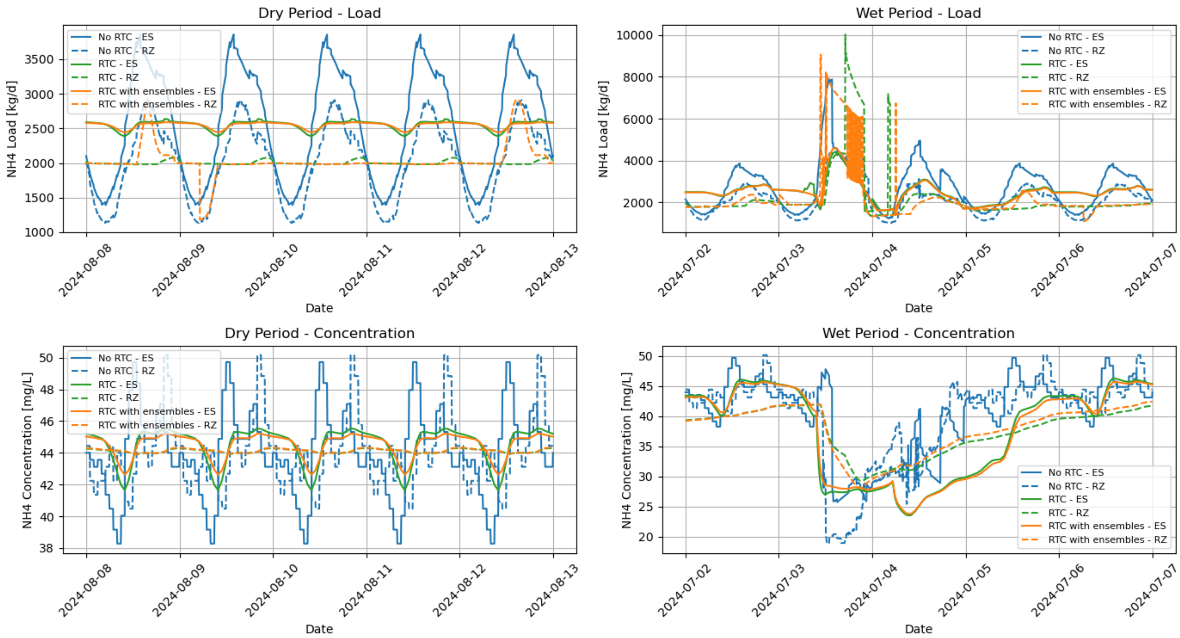


Figure 4.11: Wastewater treatment plant influent per catchment during both a period of dry weather, and during a storm event

4.4.2. Performance at Effluent

Analysing the levels of Total Nitrogen and Total Phosphorus at the WWTP effluent provides a strong indication of how well the treatment plan performs under the three different control scenarios. These effluent metrics not only reflect the plant's ability to handle changes in influent regime but also offer insight into potential surface water quality outcomes. Since the treatment process introduces outside influences to pollutant levels and alters nitrogen and phosphorus differently, both pollutants are evaluated separately to monitor their individual behaviour.

A key observation from the effluent table results (Appendix Table C.5) is the consistency between the two RTC approaches. Across the three periods, the ensemble forecast produces effluent metrics within 1% of those achieved using ideal forecasts for both TN and TP across average concentration, average load, and average daily maximum concentration–except for TN during storm events, where performance drops by 5.6%. For average daily maximum load, ensemble forecasts perform approximately 3% worse than the perfect forecasts scenario for both pollutants. Regardless, the ensemble forecast-based logic is able to achieve a reduction in daily maximum loads of more than 3% compared to the baseline, highlighting the robustness of the method despite its uncertainty in forecasts. Comparing this to findings in van der Werf et al. (2023), a larger loss in performance would be expected, where RTC performance, using real forecasts, was found to often deteriorate past that of the baseline. These differences in findings can be related to how the forecasts are used, due to their high quantitative uncertainty. Accordingly, purely identifying storm events–which the RTC used in this thesis mainly relies on–performs much better.

However, while peak effluent loads benefit from RTC, average concentration and average daily load show slight increases: TN concentration increases from 5.45 mg/L to 5.52 mg/L, and daily load from 910 kg/d to 922 kg/d. For TP, average concentration remains unchanged at 0.44 mg/L, however, the average daily load rises from 80.2 kg/d to approximately 80.8 kg/d under RTC. Despite the increase in average TN concentration, the annual average set limit of 8 mg/L, set by the UWWTD, was not reached. Similarly, since the average TP concentration remained unchanged, the set limit of 0.5 mg/L was not further approached. Although concentrations remain within limits, this rise in average TN concentration might reduce operational flexibility. Additionally, it suggests that flow-based RTC alone is insufficient, requiring either load-based RTC or adjustments of WWTP operations.

To better understand how the WWTP responds to these altered influent conditions, changes between influent and effluent metrics are analysed (Appendix Tables C.5 & C.4). Overall, the reductions observed in average daily maximum concentrations at the influent level are reflected in the effluent, suggesting that the RTC helps limit peak concentration through the treatment process. However, the expected improvements in average influent concentration and load–especially during dry weather–do not occur, despite improvements in influent quality (Table 4.12). This indicates that the WWTP is more responsive to peak flow smoothing, rather than improvements in average inflow characteristics.

Table 4.12: Comparison of objective functions of NH_4/TN & PO_4/TP levels at WWTP effluent and influent during dry conditions, where RTC stands for real-time control

		TN		**TP**	
	Scenario	**Influent**	**Effluent**	**Influent**	**Effluent**
Average concentration [mg/L]	Baseline	44.01	**4.81**	7.1	**0.38**
	RTC	42.93	4.88	6.93	**0.38**
	RTC w/ Ensemble	**42.88**	4.88	**4.92**	**0.38**
Average load [kg/d]	Baseline	4875.74	**491.65**	786.77	**39.01**
	RTC	4785.59	501.25	772.22	39.46
	RTC w/ Ensemble	**4777.76**	502.33	**770.96**	39.63

Effectively, these results show that, even though influent conditions at the treatment plant improve under both RTC strategies for both pollutants, the treatment process does not translate these improvements into lower effluent levels for all metrics. In fact, average effluent concentrations and loads in the RTC scenarios are slightly higher than those in the uncontrolled baseline scenario. This suggests that, while peak influent conditions are improved–both during dry weather and during storm events–the overall treatment efficiency is not improved. This worsening of average conditions goes back to the earlier described reasons, namely that the baseline concentrations in periods of low flow become significantly lower than the values of the RTC strategies at the same period, that averages overall become worse. As a result, the system seems more capable of reducing peak pollutant loads and concentrations than of improving average effluent levels.

Effects on other pollutants

Effluent water quality for the remaining non-prioritised pollutants is additionally monitored to prevent undesired results. Specifically, the levels of biochemical oxygen demand, chemical oxygen demand, and total suspended solids are monitored. Based on the obtained metrics for these pollutants (Appendix Table C.6), no additional negative consequences are observed. The previously observed trends carry on, where average concentration and load have minimally changed, depending on whether or not the implemented logic for the pollutant has worsened these metrics (BOD & TSS), or improved (COD). Moreover, what remains consistent is the overall improvement in the averaged daily maximum values: In all cases, the implemented RTC logic has improved these values by several per cent.

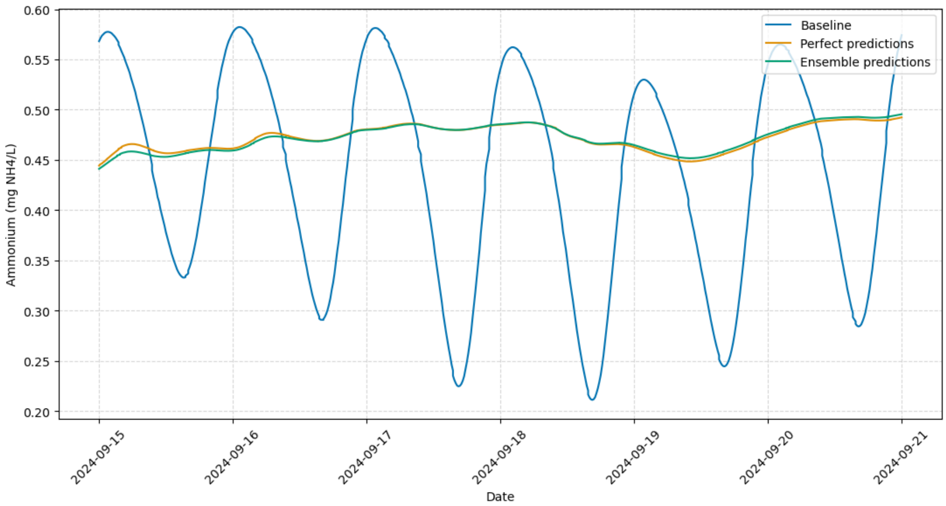
4.5. River Water Quality

The primary goal of the implemented RTC strategies is to reduce pollution impacts on the Dommel River. How the implemented controls affected the surface water quality is analysed in this sub-chapter. Due to limitations in the surface water model, only total nitrogen data are presented since phosphorus levels are unavailable in the surface water model. An important note: Since a large part of the urban drainage system was removed from the integrated model, no more CSOs can occur towards the river from any of the Eindhoven or Riool Zuid CSOs. While this is the case for all performed analyses, pollutant levels on an annual level are therefore not representative. River values during prolonged dry periods or smaller storms are still representative as no CSOs occur during these periods.

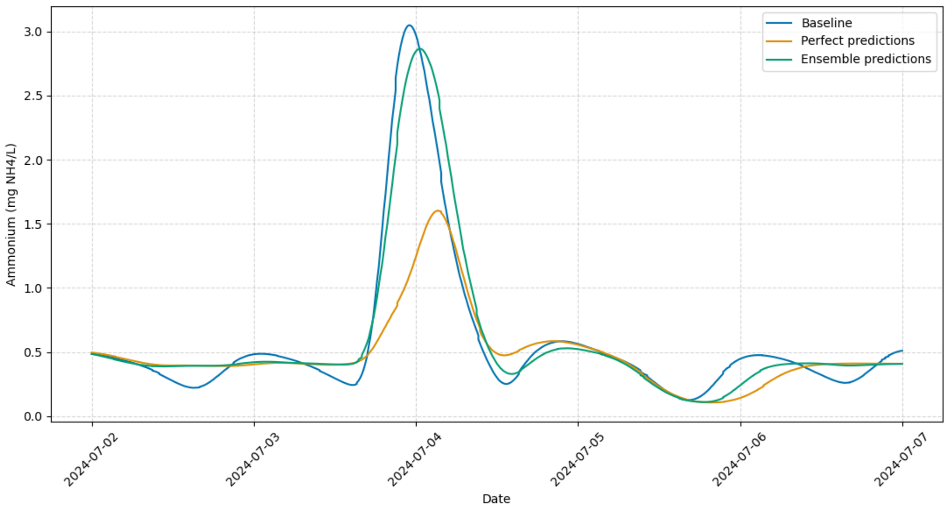
The results show that both RTC strategies lead to the same mixed outcomes as observed at the WWTP effluent (Appendix Table C.1): While both effectively reduce peak concentrations, they fail to lower the average nitrogen concentrations in the river. Despite only a small increase in WWTP effluent average TN concentration of 1.28% over the extended summer period, the river experienced a larger increase in average concentration–from 0.54 mg/L to 0.56 mg/L–representing a 3.7% rise. Relating this to the established annual average limit of 0.479 mg/L, the water quality has further declined as a result of the negative impact of the more constant WWTP influent on WWTP effluent levels.

At the same time, these dry periods also highlight the RTC's biggest positive effect: the reduction of the average daily peak values in river TN concentrations. During stable dry conditions, the daily maximum river TN concentration decreased from 0.57 mg/L to 0.48 mg/L for both RTC methods–a reduction of 15.7%. Since the variation in river load is closely related to the more highly variable TN concentration (0.2 to 0.6 mg/L), rather than variance in flow (3.7 to 4.8 m^3/s), the daily maximum load averages were reduced by a similar margin during the observed dry period. Relating the improvements in daily maximum concentrations to the established peak concentration limit of 0.763 mg/L by the ICPR and the claims by Langeveld et al. (2013) that De Dommel is sensitive to peak concentrations, a considerable improvement was reached.

This contrast–higher average concentrations alongside lower daily peaks–again reveals the core shortcoming of the RTC strategies over the evaluated period. The observed 4% increase in extended summer period average TN concentration is attributed to the flattening of the WWTP influent flow during dry weather (Figure 4.12a). While RTC successfully attenuates peak loads, it simultaneously reduces the frequency and magnitude of low-flow (and low-load) periods seen under baseline conditions, leading to worse treatment performance. As a result, any peak reduction has limited influence on average concentration or load. During the selected storm event (Figure 4.12b), a stark difference in performance between the two control logics can be observed: the perfect-forecast based control logic results in a significantly lower peak TN concentration at the river' closing section. A reason for this difference is the forecast logic in Riool Zuid (Figure 4.13). Due to the ensemble-based logic, many additional transition phases, and an early WWF mode are triggered. Consequently, differences are created in load which lead to lower peak effluent values and river water quality levels.



(a) During a 7-day dry weather period, the RTC has an impact on average concentrations and reduces minor peaks.



(b) During a storm event, the perfect forecast RTC dramatically reduces the peak TN concentration

Figure 4.12: Simulated TN concentration in the Dommel river, comparing the baseline against the perfect and ensemble RTC models.

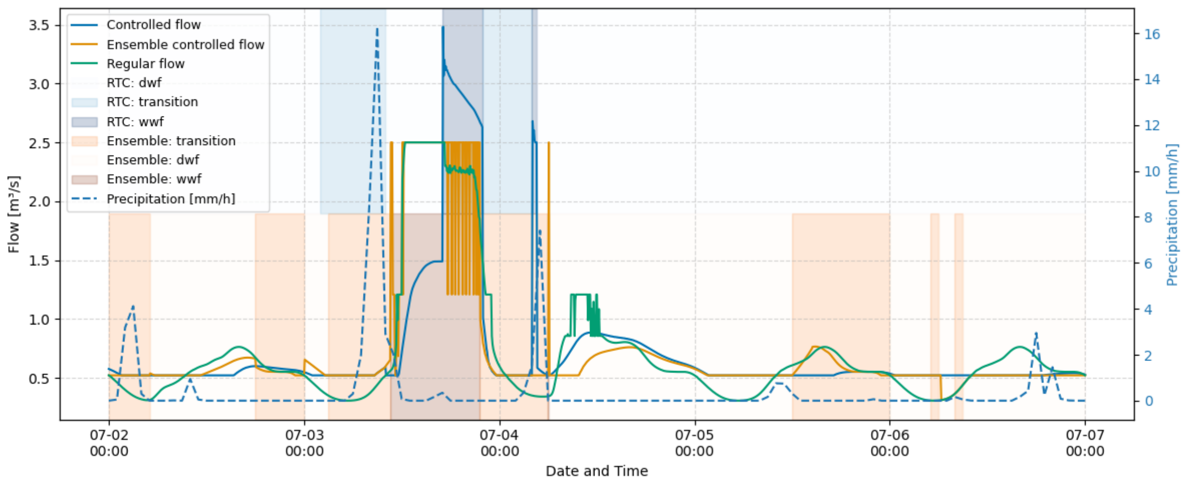


Figure 4.13: Difference in operational modes to the upcoming storm event in Riool Zuid

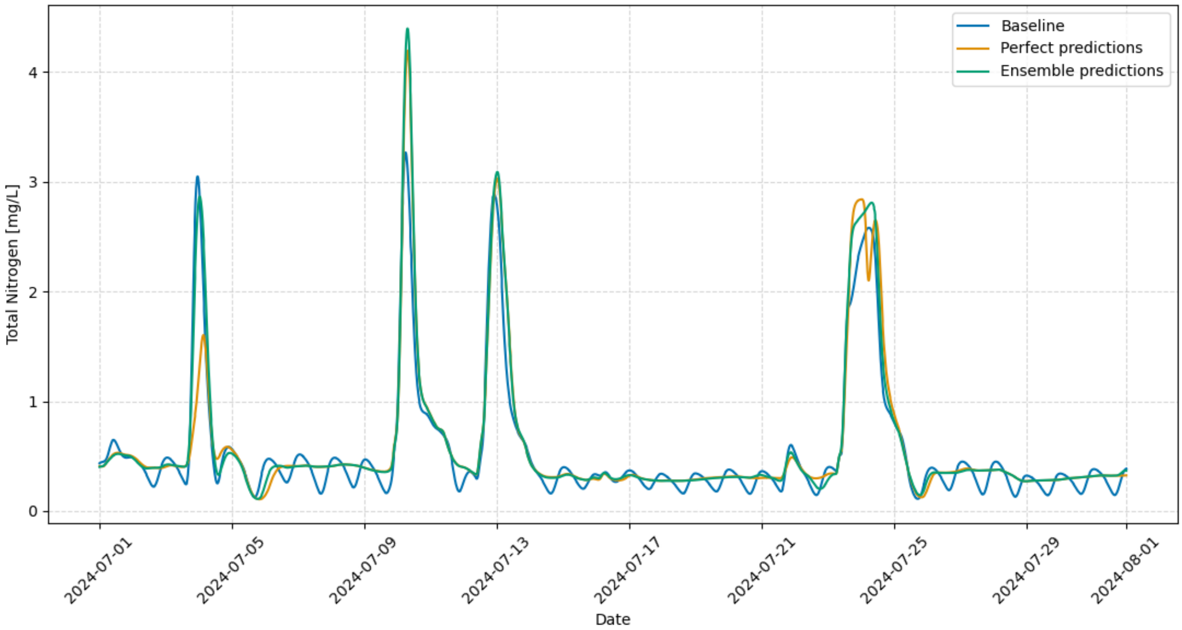
Conclusively, for surface water quality purposes, the implementation of the RTC logic had an overall negative effect on passing the surface water quality limits. Despite this, lower TN peak concentrations can reduce nitrogen toxicity, improve dissolved oxygen levels, and limit algae growth–key indicators of better surface water quality. Furthermore, during the evaluated storm event, the RTC strategies–especially under perfect forecasts–appear to be able to significantly reduce peak ammonium concentrations by pre-emptively emptying the catchment storage units. This reduced the inflow of highly concentrated wastewater during high-flow, low retention-time conditions at the WWTP, thus improving treatment performance during critical events, leading to better surface water quality.

Additionally, to check the effect of the implemented control logic, the dissolved oxygen levels at the closing section of the river are evaluated. This final evaluation tests if less fluctuation in WWTP influent can potentially lead to better overall water quality for microorganisms, aquatic life, and less algae bloom. With the implemented control logic, both performing on equal level, the average concentration and load are slightly lower–accordingly to a small increase in average TN concentrations (Table 4.13). Other (positive) changes are observed in the average daily minimum concentrations and loads. The daily minimum concentration over the entire period was improved by 1%, an increase in average minimum daily value of 2% is noted during the dry period, and lastly, the average daily minimum loads are improved by about 5%. The discontinuity between the improvement in the daily minimum concentration and load can be attributed to a change in WWTP effluent flow. Since this flow is more constant, fewer fluctuations are created in De Dommel's flow, as the WWTP's effluent can contribute up to 50% to the total flow in the river.

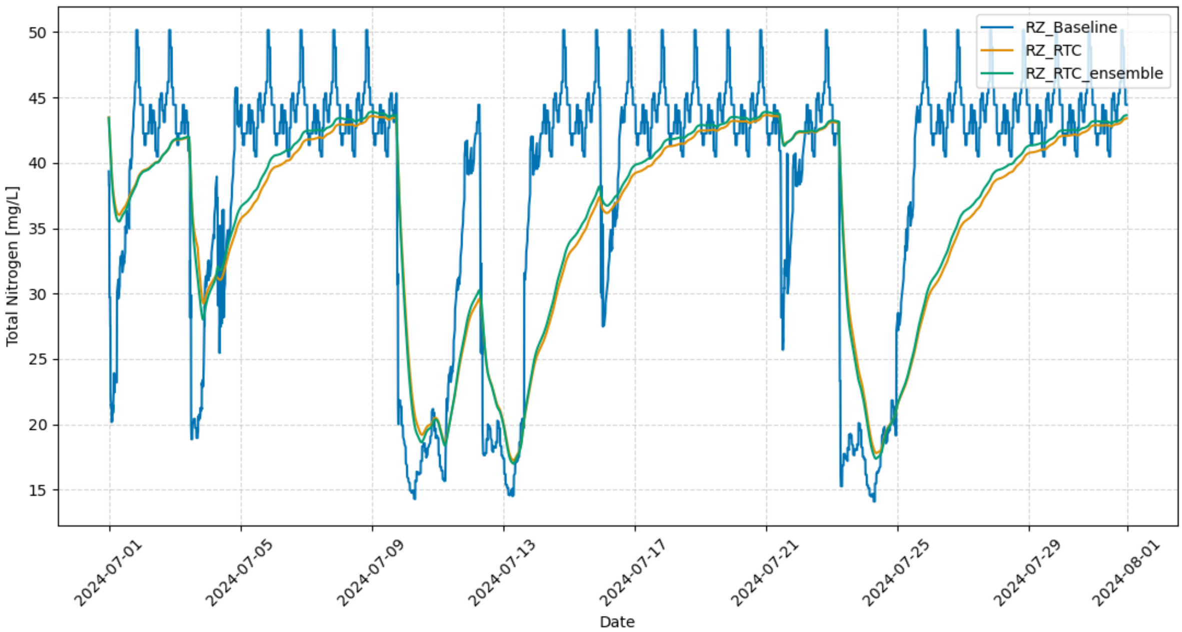
Table 4.13: Comparison of objective functions of Dissolved Oxygen levels at the closing section of De Dommel. Where average load and concentration are monitored, as well as the average of the daily minimum concentration and load

Metric	Scenario	Entire period	Dry	Wet
Average concentration [mg/L]	Baseline	**6.9**	**7.19**	**6.59**
	RTC	6.88	7.17	6.55
	RTC w/ Ensemble	6.89	7.17	6.55
Average load [kg/d]	Baseline	2266.49	1803.83	1975.47
	RTC	**2273.39**	1811.38	1985.94
	RTC w/ Ensemble	2271.23	**1812.4**	**1986.9**
Average daily minimum concentration [mg/L]	Baseline	6.15	6.78	5.94
	RTC	**6.21**	**6.93**	5.83
	RTC w/ Ensemble	6.18	**6.93**	**6.04**
Average daily minimum load [kg/d]	Baseline	1990.99	1651.73	1739.85
	RTC	**2069.7**	1732.85	1810.53
	RTC w/ Ensemble	2050.22	**1734.3**	**1813.23**

Lastly, while all wet weather flow results are based on a single selected storm event–as continuously evaluating all storm events was out of the scope–the three storm events succeeding the previously evaluated storm event were evaluated to check for result consistency. When analysing the effects of total nitrogen concentration of the three other storm events, inconsistencies with the above were observed (Figure 4.14a). In all cases, river concentrations are instead worsened as a result of the implemented RTC logic rather than improved. This particular difference originates from the Riool Zuid catchment, where during and after storm events, concentrations deviate by a large degree from the baseline (Figure 4.14b). Initially, it was hypothesised that this difference was caused by an error in pollutant levels in the baseline scenario at the outflow point of the catchment. It was tested whether the used dry weather inflow pattern was incorrect, or whether the absence of the continuously mixed reactor in the baseline caused this. However, neither hypothesis led to significant changes to the baseline wet weather flow and was therefore declined. Further analysis showed that, during the three storm events where river pollution levels were worse, the Riool Zuid catchment had the exact same water outflow levels in all scenarios, indicating no effect of the implemented RTC on volume flows during these storm events. The exact cause of the significant differences in pollution concentrations in these events remains unclear.



(a) Total nitrogen concentration at the closing section of the Dommel



(b) Total nitrogen concentration leaving the Riool Zuid catchment

Figure 4.14: Analysis of TN concentrations during multiple storm events in during the month of July

5 Discussion

The evaluation of the three sensitivity scenarios–the Baseline (uncontrolled), real-time control with perfect forecasts, and real-time control using ensemble forecasts–revealed both clear improvements and trade-offs when RTC was applied. Both the perfect forecast RTC and the ensemble-based forecast RTC achieved significantly flatter catchment outflows compared to the baseline, with flow remaining within +/- 5% of the ideal flat rate during up to 70% of dry weather periods. The ensemble-based strategy showed a conservative bias in its precipitation predictions, favouring false positives over false negatives. This resulted in more frequent disruptions to the ideal constant catchment outflows–reducing flat-flow rate from 70% to approximately 55% in the worst scenario–but did not lead to significant negative impacts on system performance or water quality. In the Eindhoven catchment, the RTC strategies led to a substantial reduction in CSO volumes, as the system's single downstream storage unit could be pre-emptively emptied prior to storm events. In contrast, the impact in the Riool Zuid catchment was minimal, primarily due to system layout: most CSOs in Riool Zuid are located further upstream and are not directly connected to or affected by the controlled storage unit of this catchment. Although influent flow flattening improved average WWTP influent characteristics, these benefits did not consistently carry over to effluent or receiving water quality metrics. This difference was especially noticeable in average concentration and load: Although influent values improved by approximately 2% with RTC, effluent averages were increased by 1.5%. This effect was largely due to the lack of periods of low flow in the RTC scenarios: The baseline scenario, with its periods of low flow during the night, promoted different internal recirculation in the treatment plant, thereby improving effluent quality during those intervals and reducing daily average values. In contrast, daily peak concentrations and loads improved consistently across influent, effluent, and surface water, showing reductions of around 5% on average due to RTC implementation. These results suggest that, within the currently modelling setup, RTC of dry weather flow is effective at mitigating peak concentrations and loads. However, it does not necessarily enhance average effluent or surface water quality–and in some cases, may worsen it. This distinction is particularly relevant, as most regulatory and environmental performance criteria for WWTP effluent and surface water are based on annually averaged metrics, rather than daily peaks.

While most RTC applications in urban wastewater systems focus on reducing CSOs during storm events, a smaller set of work has explored RTC as a means to improve WWTP effluent quality–particularly under dry weather conditions. In much of the existing literature, such as Seggelke et al. (2013) and Dirckx et al. (2011), RTC strategies are primarily designed around hydraulic performance, targeting CSO volume, flood prevention, and operational stability of WWTPs. These studies apply simulation-based or fuzzy-logic control to control inflows or manage storage levels, but largely treat water quality as a secondary, or indirect, effect rather than a primary design criterion. For example, the Wilhelmshaven case (Seggelke et al., 2013) implemented an integrated fuzzy-rule-based RTC system across sewer and treatment plant components, successfully reducing CSO events and managing critical WWTP clarifier conditions. However, this system was reactive and deterministic, lacking the predictive control or pollutant-centric evaluation that is central to this thesis. Similarly, Dirckx et al. (2011) analysed RTC through a cost-efficiency lens, evaluating economic viability for CSO impact reduction, but with little attention to long-term pollutant dynamics or effluent quality outcomes. In contrast, studies such as Seggelke et al. (2005), Langeveld et al. (2013), van Daal-Rombouts, Benedetti, De Jonge, et al. (2017), and Troutman et al. (2020) adopt a more process-informed and quality-oriented view of RTC. For instance, Seggelke et al. (2005) aimed to improve WWTP effluent quality by running a parallel online simulation of the treatment plant to determine optimal inflow conditions. Inflow levels were calculated using a hydrological model (KOSIM) that translated current precipitation into runoff estimates, thereby allowing control of upstream flows. As this study focused primarily on wet weather scenarios, the analysis focused on reductions in peak ammonium concentrations. Langeveld et al. (2013) offers a more impact-driven and integrated control logic showing that pollutant concentration improvements in the Dommel River can be achieved by aligning RTC with surface water quality targets. Still, the approach prioritised wet-weather control and does not have a particular focus on dry weather controls. van Daal-Rombouts, Benedetti, De Jonge, et al. (2017) explores smart buffer management in storm water retention tanks, showing improvements in NH_4^+ conditions during storm events in both the catchment and WWTP. Yet, this study also focuses on wet weather events and does not distinguish or assess dry weather flow optimisation. Troutman et al. (2020) uses the sewer system as a dynamic extension of the WWTP and shows that flattening inflow oscillations–through in-sewer storage–can improve settling and reduce short-term treatment disruption. However, the method remains deterministic and sensor-driven, without the use of forecasts or flow regime classification.

While most RTC studies rely on historical or deterministic rainfall forecasts, few account for the uncertainty introduced by real-world precipitation forecasts–particularly under dry conditions. Seggelke et al. (2005) demonstrated simulation-based inflow control using perfect forecast knowledge, but without addressing forecast uncertainty. More recent work, such as van der Werf et al. (2023), included forecast reliability into the predictive heuristic control framework, translating varying nowcast accuracy into risk-based control actions. Similarly, Courdent et al. (2018) showed that ensemble-based forecasts can classify flow regimes up to 48 hours ahead, though their use remains largely confined to wet-weather control. These studies emphasise storm-driven events and CSO avoidance, rather than exploiting the knowledge that no storm events are upcoming.

In contrast to previous work, this study applies ensemble forecasts-based RTC specifically for control in dry weather conditions to optimise inflow flattening and indirectly improve effluent quality. The results show that forecast information, to predict the start of storm events, is sufficient to implement effective RTC. By explicitly accounting for forecast uncertainty, the ensemble-based approach introduces a conservative bias to prevent additional CSOs in favour of less effective control. This approach moves beyond earlier heuristic or model predictive strategies by integrating probabilistic information into a quality-focused control objective. As such, the findings link two areas that have so far remained largely separate–forecast-informed control and dry-weather effluent quality optimisation.

Moreover, this study has demonstrated that RTC can significantly improve dry weather flow management. Using both ideal and ensemble-based forecasts, flow variability was reduced, achieving near-constant inflow to the WWTP during dry periods. Pre-emptive emptying of buffer storage proved so effective that CSO volumes were reduced, despite increased buffering–a result particularly evident in Eindhoven, where only a single storage unit was used. The ensemble-based forecasts, while quantitatively inaccurate in precipitation amounts, proved qualitatively sufficient to identify rainfall timing and trigger transitions effectively. This shows that high-accuracy rainfall prediction is not a prerequisite for RTC to trigger state changes, enhancing the real-world feasibility of implementing such systems. Most importantly, effluent quality improved in terms of peak values as a result of the implemented RTC, contributing to a reduced risk of ammonia-related toxicity. Despite this, environmental regulations were not met or improved, as the average effluent quality, especially for total nitrogen, degraded due to differences in WWTP performance. However, the method was proven to be effective in peak load and concentration attenuation. The noted contrasting performance between the Eindhoven and Riool Zuid catchments illustrates the need for tailored control strategies based on system layout, storage structure, and hydraulic response times. This suggests that while the overall method is transferable, its success depends on local calibration and model integration. Further, this study highlights the importance of forecast-informed control logic that incorporates uncertainty, offering a promising direction for more optimised usage of the wastewater systems. To implement such strategies in practice, utilities would require scalable control systems, daily-updated weather forecast integration, and real-time measurement data capability. While this infrastructure may already exist in well-modelled and instrumented areas, adoption in smaller municipalities would require investments.

Despite promising results, this study is subject to several limitations related to model accuracy, scope, and makes assumptions that affect the wider applicability of this research and its conclusions. This study relies on a simplified UDS model derived from an already simplified WEST model, making it a ”simplification of a simplification.” This increases the risk of flow and storage inaccuracies and omits detailed control interactions. Additionally, the Eindhoven and Riool Zuid CSOs in the WEST model were decoupled, limiting the river quality assessment’s representativeness, especially during wet periods. While there is uncertainty in river water quality due to pollutant sources, they still allow for relative performance comparisons. Simulations were restricted to the dry extended summer period, potentially overestimating the effectiveness of dry-weather-focused RTC. Furthermore, no adjustments were made to WWTP operations and parameters in response to the change in inflow regime, underestimating potential effluent gains. Both catchments were treated similarly despite their differing (spatial) characteristics, which may have affected control and forecast performance. DWF was assumed to have a steady pattern throughout, whereas a real implementation would require more adaptive controls. Additionally, the empirical water quality model–already limited in accuracy–fails to capture storm-related pollutant peaks accurately, partly due to issues from the transfer to Python, affecting the reliability of results during transition and wet weather periods. Another aspect to consider is the analysis of the required time to empty: A constant additional flow was assumed in this analysis rather than a gradually increasing flow. Moreover, the effects of pre-emptively emptying on WWTP operations and effluent quality could not be tested, as no suitable approach was found. Lastly, during the latter stages of the project, inconsistent results in Riool Zuid’s pollutant outflow during the storm events that followed the primarily evaluated storm event were observed. Consequently, WWF results based on the primary evaluated storm event cannot be deemed representative of all storm events.

Ultimately, this study presents a system-wide evaluation of RTC strategies for DWF management, applied under realistic ensemble-based weather forecasts. While most RTC research focuses on storm-driven overflow prevention, this work shifts the focus to WWTP effluent quality optimisation during dry weather conditions. By integrating rainfall forecasts into control logic and simulating the effects of buffering on pollutant concentrations, the study demonstrates that nitrogen and phosphorus peak load and concentration reductions are achievable under dry periods. The work contributes a forecast-informed, heuristic-rule-based RTC framework that is both implementable within existing infrastructure and sensitive to catchment-specific dynamics, highlighting its applicability across various urban wastewater systems.

A key insight from this study is the role of ensemble-based forecasts, allowing for more traditionally risky RTC approaches, without any additional risk or immediate drawbacks. In this case, wastewater is actively buffered in the urban drainage system–reducing storm water storage capacity–without increasing CSO frequency or volume. An additional insight from this study is the role of upstream municipal infrastructure in creating more favourable (stable) operation conditions for downstream WWTPs, which are typically managed by regional waterboards. This reveals an important opportunity for more integrated governance in the urban wastewater system, where coordinated RTC can align multiple objectives across governance bodies. In the context of climate-induced dry spells and tightening water quality regulations, such cooperation is increasingly vital for ensuring both ecological protection and operational sustainability of wastewater systems.

6 Conclusion

In this study, the impact of controlling dry weather flow on the effluent quality of the Eindhoven wastewater treatment plant and the receiving water quality was assessed. To achieve this, simplified bucket models of the Eindhoven and Riool Zuid catchments were created using EPA's Storm Water Management Model. An empirical water quality model was (re)implemented for better pollutant behaviour replication, and a PySWMM-based control script was designed to manage pump operations according to identified weather scenarios and pre-defined operational modes. The resulting outflows from the urban drainage systems were then used as inputs for a WEST-based WWTP model, allowing the evaluation of the resulting effluent quality. The main findings of this project are:

- **Real-time control can achieve a reduction in daily peak loads and concentrations:** Despite certain limitations–such as model simplifications with the drainage system, limited weather data availability, and static WWTP controls and parameters–the study demonstrates that smoothing dry weather flow fluctuations can be an effective strategy to reduce ammonium and phosphorus peak concentrations and loads in the WWTP effluent.
- **Well-managed in-sewer dry weather storage leads to no additional risk:** With the addition of pre-emptively discharging the stored wastewater in case of detection of an upcoming storm event, in-sewer storage levels were minimised at the start of storm events, preventing additional CSO risk.
- **Ensemble forecasts negatively impact RTC decision-making quality:** Although more incorrect predictions were observed–especially in spatially complex catchments such as Riool Zuid–the forecasts were generally reliable for identifying dry weather periods and triggering scenario-based controls. These results highlight the practical applicability of ensemble-based forecasts in RTC strategies. With more refined, catchment-specific thresholds and decision rules, further improvements in outflow stability and effluent quality could likely be achieved.
- **Changed influent regime requires additional WWTP tuning:** Despite the fact that all metrics–both average and peak concentration as well as load–improved at the influent of the treatment plant, the average effluent quality degraded, especially in dry weather scenarios. This degradation was caused by the additional recirculation during night periods as a result of the implemented RTC, leading to much lower minimum outgoing concentrations, with higher averages as a result.

Ultimately, this research has shown the potential of RTC in urban drainage systems to cross shareholder boundaries by providing beneficial conditions for downstream WWTPs. Despite using uncertain forecasts, clear improvements in effluent quality are achievable, providing a clear answer to the central research question: Ensemble-based RTC of dry weather flow can improve influent stability to the Eindhoven WWTP and reduce peak effluent and surface water conditions. These results offer a starting point for both urban drainage infrastructure and wastewater treatment plant stakeholders to improve surface water ecology through a combined effort. While further improvements and a more integral approach are needed, the groundwork laid here showcases another step forward to a more integral, smarter, and more resilient urban wastewater management.

7 Future Research

While this study offers valuable initial insights into the potential of DWF attenuation, several opportunities remain for future research. In this thesis, a heuristic control strategy was applied to flatten the flow to the WWTP by stabilising DWF. While effective as a proof of concept, this approach has several limitations that future research could address to improve system performance and robustness:

- **Control based on pollutant load:** Future studies could shift from controlling flow to directly controlling outgoing pollutant load from the catchment. This would require a more complex balance between outgoing flow, stored volume, and pollutant concentrations. Since diurnal concentration patterns differ between pollutants–and often deviate from flow patterns–an optimization-based control framework would be required.
- **Catchment-specific control logic:** The current approach applies uniform control across catchments with different physical layouts, CSO behaviour, and travel time dynamics, where distinction between catchments is primarily made by use of different parameters. Developing tailored strategies that better reflect the hydrological and spatial characteristics of each catchment could improve results, especially under uncertain forecast conditions in more complex catchments.
- **Model predictive control:** This thesis uses a heuristic rule strategy which offers simplicity and interpretability but lacks the adaptability and predictive power of the optimization-based model predictive control. This control strategy is more dynamic and is able to both better react and anticipate current and future system states, ultimately improving reliability and performance. Concurrently, model predictive control can be more generally applied to different catchments, without requiring complex fine-tuning of individual rules.

While this thesis builds on an integrated model that includes a UDS, WWTP, and receiving waters, this integration is disrupted in the current setup. The UDS was uncoupled and re-modelled in SWWM for the purpose of implementing RTC, which removed both its direct influent on the river through CSOs and its feedback interactions with the treatment plant. This uncoupling reduces the accuracy of downstream impacts and limits the ability to evaluate system-wide control interactions. To address this, future work should focus on re-establishing an integrated modelling framework that includes:

- **Integrated model with RTC:** Identifying a modelling package that supports RTC within a fully coupled urban drainage-WWTP-river system would enable assessment of system-wide effects, including CSO impacts, seasonality, and feedback-driven optimisation.
- **Feedback between treatment plant and drainage system:** Beyond basic integration, introducing additional feedback mechanisms between the treatment plant and the drainage system would allow for more holistic optimisation. Which could improve effluent quality, reduce CSO and flooding risks, and support mode adaptive and efficient WWTP operation.
- **Model analysis based on a set of representative storm events:** Since storm events are highly varying in intensity and duration, a representative set including a spectrum of storm events ought to be used for model verification.

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A
Modelling Structure

A.1. Urban Drainage Model

A.1.1. Universal Subcatchment Parameters

Table A.1: Universal subcatchment parameters based upon best fit with case study flow regime

Category	**Value**
Depression Storage [mm]	2
Evaporation Pattern [mm/15min]	From case study
Area Impervious [%]	100
Impervious Area without Storage [%]	0
Catchment Slope [%]	2
Infiltration Method	Horton (default parameters)

B

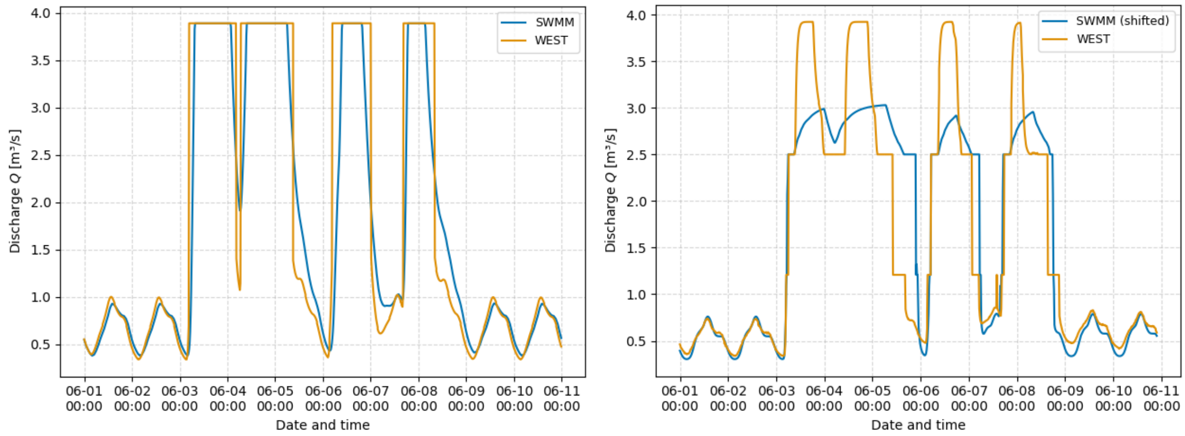
Model & Data Analysis

B.1. Urban Drainage Model

B.1.1. Schematic Overview

Figure B.1: Urban drainage system architecture in SWMM, with the Eindhoven catchment in the top-left, Geldrop and Mierlo on the very right, and bottom (left) being everything upstream of the Aalst pumping station. Connecting the latter 3 is the fully hydrodynamically implemented transport pipe. Four rain gauges are placed on the very left.

B.1.2. Wet Weather Flow



(a) Eindhoven catchment
NSE = 0.857, RMSE=0.576 m^3/s

(b) Riool Zuid, SWMM model time-shifted backwards by 2.5 hours
NSE = 0.775, RMSE = 0.593 m^3/s

Figure B.2: Catchment exit pump flow comparison between SWMM and WEST model per catchment during a wet period

B.1.3. Water Quality Model

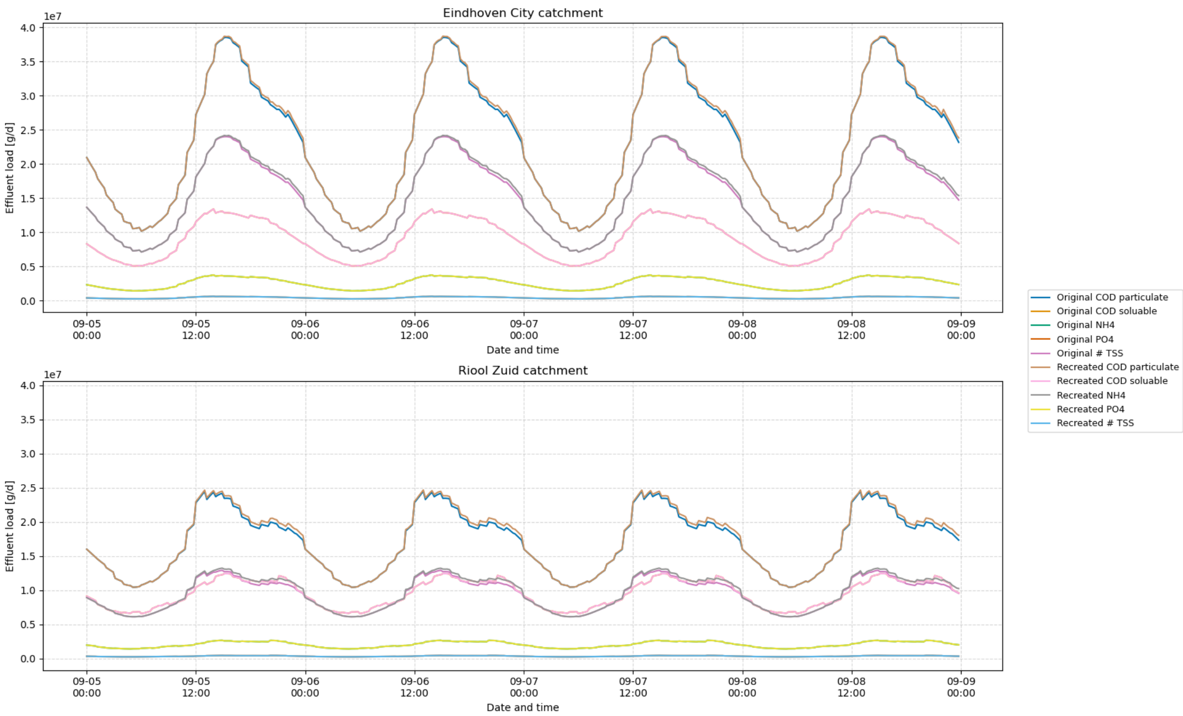


Figure B.3: Comparison of effluent concentration between the original water quality model in WEST, and the recreated water quality model in Python

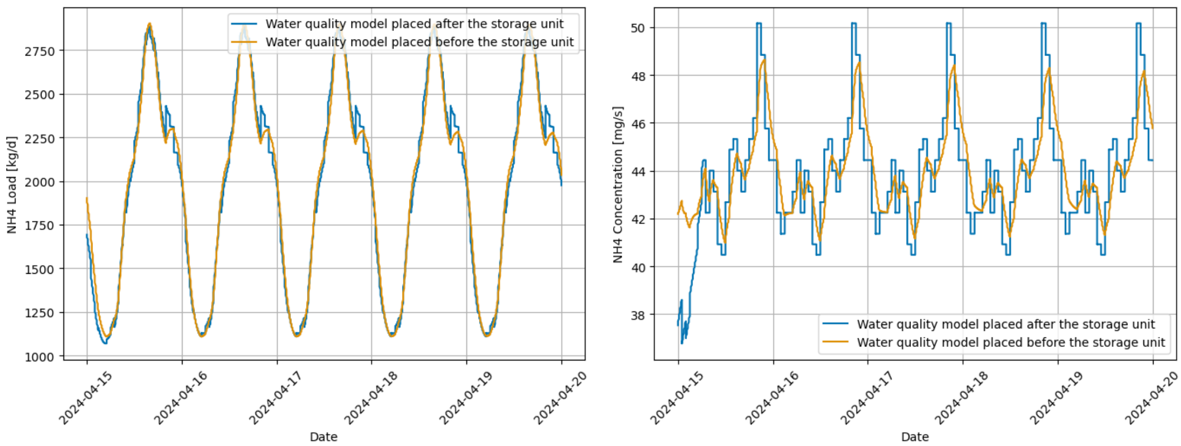


Figure B.4: Difference in NH4 load and concentration at the effluent point of the Riool Zuid catchment (SWMM), when placing the water quality model before or after the storage of the transport pipe at the downstream end of Riool Zuid

B.2. System Characteristics and Capacities

B.2.1. Time to Empty

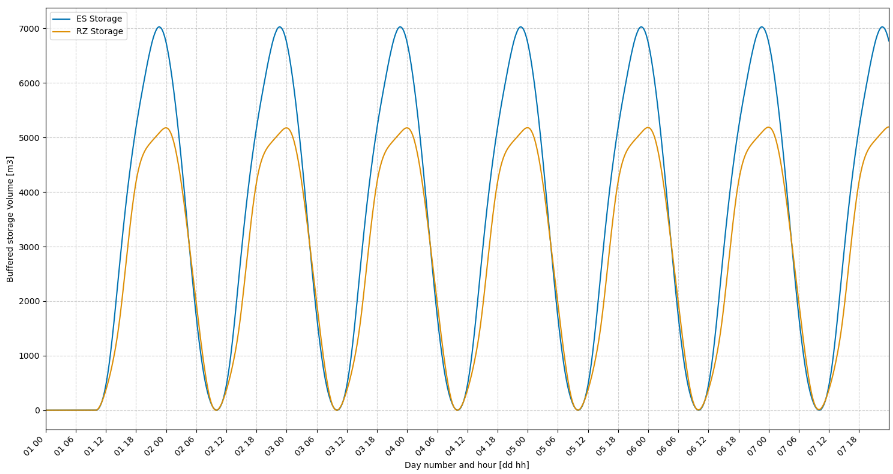


Figure B.5: Theoretical buffer volume patterns under dry weather conditions, with variable inflow and constant outflow. This illustrates the filling and empting of storage volume based on inflow changes

B.2.2. System Characteristics

Operational Characteristics

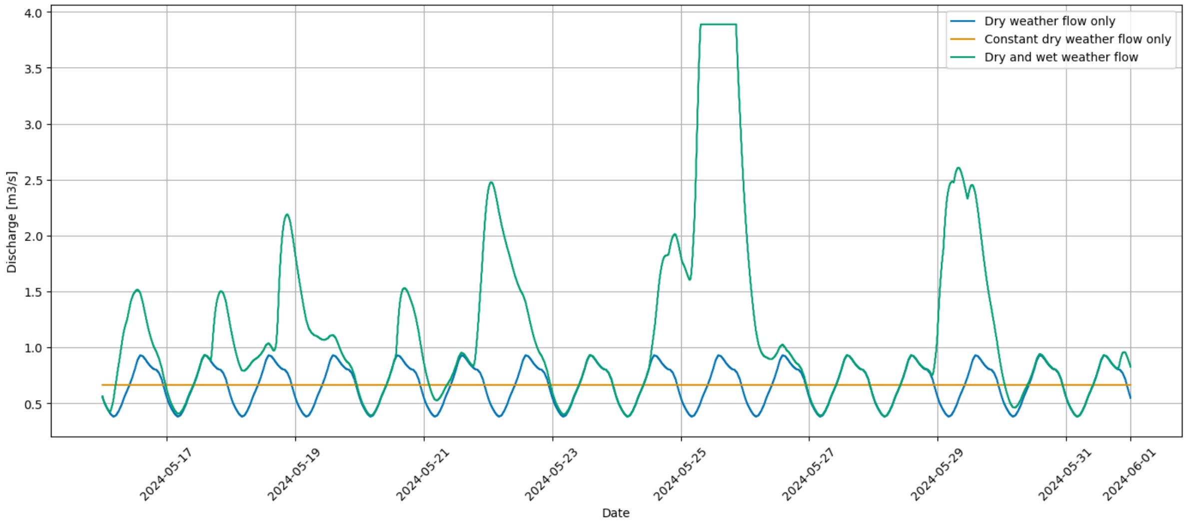


Figure B.6: Outflow from the Eindhoven City catchment under the three scenarios. The DWF only scenario has 5 % metric score of 13.09, the constant scenario a perfect 1, and the DWF and WWF scenario a score of 15.11.

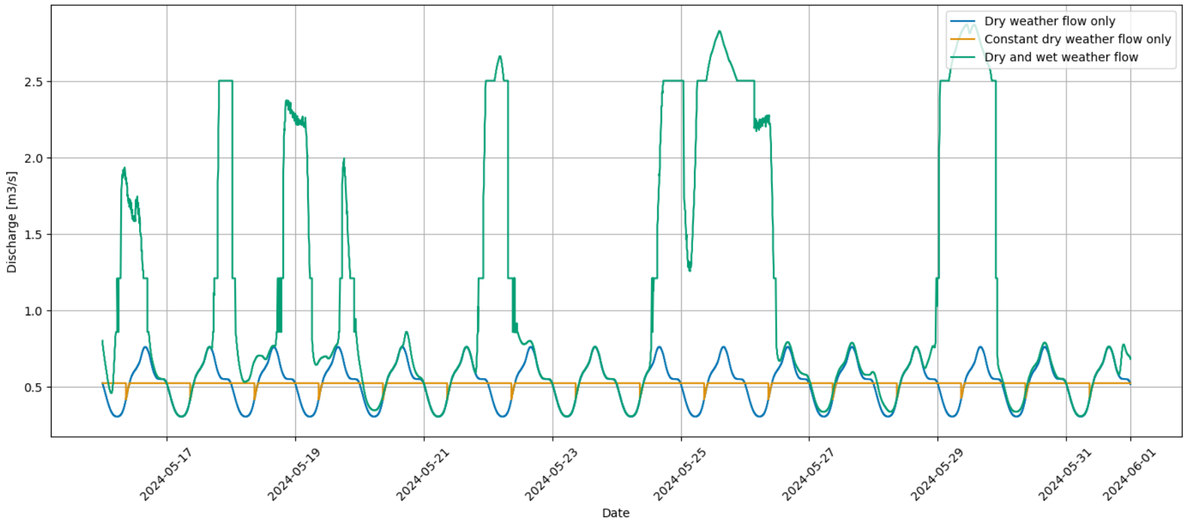


Figure B.7: Outflow from the Riool Zuid catchment under the three scenarios. The DWF only scenario has 5 % metric score of 9.53, the constant scenario a perfect 1, and the baseline scenario a score of 13.75.

C

Performant Real-Time Control

C.1. Performant Metrics at Closing Section of River

Table C.1: Pollutant river

Metric	Scenario	Entire period	Dry	Wet
Average concentration [mg/L]	Baseline	**0.54**	**0.46**	0.57
	RTC	0.56	0.48	**0.47**
	RTC w/ Ensemble	0.56	0.48	0.56
Average load [kg/d]	Baseline	**332.88**	**171.43**	289.47
	RTC	340.75	175.81	**224.31**
	RTC w/ Ensemble	341.96	176.1	280.33
Average daily maximum concentration [mg/L]	Baseline	0.85	0.57	1.35
	RTC	**0.79**	**0.48**	**0.78**
	RTC w/ Ensemble	0.82	**0.48**	1.25
Average daily maximum load [kg/d]	Baseline	594.98	225.43	849.92
	RTC	**552.71**	**179.14**	**449.48**
	RTC w/ Ensemble	574.43	179.15	774.69

C.2. Remaining Performant Metrics

Table C.2: Pollutant outflow metrics of the Eindhoven catchment

		NH			PO4		
Metric	**Scenario**	**Entire period**	**Dry**	**Wet**	**Entire period**	**Dry**	**Wet**
Average concentration [mg/L]	Baseline	40.94	44.03	41	6.61	7.11	6.62
	RTC	40.56	44.35	38.63	6.55	7.16	6.23
	RTC w/ Ensemble	**40.47**	**43.94**	**38.55**	**6.53**	**7.09**	**6.22**
Average load [kg/d]	Baseline	2766.86	2488.39	2643.94	446.47	401.54	426.64
	RTC	2709.84	2543.73	2517.58	437.27	410.47	406.25
	RTC w/ Ensemble	**2703.92**	**2520.53**	**2515.12**	**436.31**	**406.72**	**405.85**
Average daily maximum concentration [mg/L]	Baseline	47.57	48.9	47.13	7.68	7.89	7.6
	RTC	43.68	44.86	42.74	7.05	7.24	6.9
	RTC w/ Ensemble	**43.39**	**44.45**	**42.4**	**7**	**7.17**	**6.84**
Average daily maximum load [kg/d]	Baseline	4283.37	3605.89	4420.08	691.18	581.86	713.24
	RTC	**3294.7**	2623.72	**3075.93**	**531.64**	423.37	**496.34**
	RTC w/ Ensemble	3354.44	**2599.07**	3088.44	541.28	**419.4**	498.36

Table C.3: Pollutant outflow metrics of the Riool Zuid catchment

		NH			PO4		
Metric	**Scenario**	**Entire period**	**Dry**	**Wet**	**Entire period**	**Dry**	**Wet**
Average concentration [mg/L]	Baseline	39.98	44.06	40.7	6.45	7.11	6.57
	RTC	**38.6**	**40.94**	**38.21**	**6.23**	**6.61**	**6.17**
	RTC w/ Ensemble	38.78	41.33	38.58	6.26	6.67	6.22
Average load [kg/d]	Baseline	**2233.6**	2007.52	**2133.22**	**360.42**	323.94	**344.22**
	RTC	2278.46	**1863.67**	2156.49	367.66	**300.73**	347.98
	RTC w/ Ensemble	2278.45	1878.85	2200.34	367.66	303.18	355.05
Average daily maximum concentration [mg/L]	Baseline	47.9	49.34	47.52	7.73	7.96	7.67
	RTC	**40.82**	**41.61**	**40.39**	**6.59**	**6.71**	**6.52**
	RTC w/ Ensemble	41.07	41.98	40.94	6.63	6.77	6.61
Average daily maximum load [kg/d]	Baseline	**3319.38**	2782.59	**3061.92**	**535.63**	449.01	**494.08**
	RTC	3896.3	**1949.15**	4174.45	628.72	**314.52**	673.6
	RTC w/ Ensemble	4222.18	1958.01	4092.85	681.31	315.95	660.44

Table C.4: Pollutant influent metrics wwtp

		NH			PO4		
Metric	**Scenario**	**Entire period**	**Dry**	**Wet**	**Entire period**	**Dry**	**Wet**
Average concentration [mg/L]	Baseline	39.81	44.01	40.26	6.42	7.1	6.5
	RTC	**39.16**	42.93	**38.2**	**6.32**	6.93	**6.16**
	RTC w/ Ensemble	39.17	**42.88**	38.31	**6.32**	**6.92**	6.18
Average load [kg/d]	Baseline	5514.89	4875.74	5290.57	889.9	786.77	853.71
	RTC	5504.13	4785.59	**5189.53**	888.17	772.22	**837.4**
	RTC w/ Ensemble	**5497.82**	**4777.76**	5227.28	**887.15**	**770.96**	843.49
Average daily maximum concentration [mg/L]	Baseline	45.04	46.74	45.06	7.27	7.54	7.27
	RTC	42	43.54	**41.57**	6.78	7.03	**6.71**
	RTC w/ Ensemble	**41.96**	**43.48**	41.67	**6.77**	**7.02**	6.72
Average daily maximum load [kg/d]	Baseline	7860.71	6586.19	7880.35	1268.43	1062.77	1271.6
	RTC	**7183.08**	4959.68	7251.4	**1159.09**	800.31	1170.11
	RTC w/ Ensemble	7389.05	**4938.92**	**6659.47**	1192.32	**796.96**	**1074.6**

Table C.5: Pollutant effluent metrics WWTP

		TN			TP		
Metric	**Scenario**	**Entire period**	**Dry**	**Wet**	**Entire period**	**Dry**	**Wet**
Average concentration [mg/L]	Baseline	**5.45**	**4.81**	4.85	**0.44**	**0.38**	**0.39**
	RTC	5.52	4.88	**4.72**	**0.44**	**0.38**	**0.39**
	RTC w/ Ensemble	5.52	4.88	4.84	**0.44**	**0.38**	**0.39**
Average load [kg/d]	Baseline	**910.49**	**491.65**	716.22	**80.18**	**39.01**	58.12
	RTC	922.15	501.25	**675.46**	80.75	39.46	57.94
	RTC w/ Ensemble	925.3	502.33	720.19	80.98	39.63	**57.58**
Average daily maximum concentration [mg/L]	Baseline	6.63	5.09	5.88	0.54	0.41	0.46
	RTC	**6.37**	**4.91**	**5.34**	**0.53**	**0.39**	0.46
	RTC w/ Ensemble	6.42	**4.91**	5.66	0.54	**0.39**	**0.44**
Average daily maximum load [kg/d]	Baseline	1794.88	695.26	1384.56	159.16	56.65	102.86
	RTC	**1640.94**	535.69	**1120.76**	**148.27**	42.14	107.2
	RTC w/ Ensemble	1693.56	**530.16**	1175.16	153.53	**41.86**	**90.48**

Table C.6: Pollutant effluent metrics of other pollutants

		BOD			COD			TSS		
Metric	**Scenario**	**Entire period**	**Dry**	**Wet**	**Entire period**	**Dry**	**Wet**	**Entire period**	**Dry**	**Wet**
Average concentration [mg/L]	Baseline	**1.77**	**1.38**	**1.49**	31.56	33.94	29.73	**4.96**	**4.13**	**4.51**
	RTC	1.79	1.41	1.52	**31.21**	32.22	28.97	**4.96**	4.18	4.59
	RTC w/ Ensemble	1.8	1.41	1.51	31.24	**32.11**	**28.89**	4.99	4.17	4.58
Average load [kg/d]	Baseline	**390.31**	**143.76**	**218.89**	4739.39	3452.06	3945.87	966.06	430.19	664.21
	RTC	392.04	144.97	218.96	**4725.62**	3306.09	**3919.16**	**939.02**	**429.53**	**662.06**
	RTC w/ Ensemble	397.05	144.92	220.25	4745.91	**3305**	3939.61	958.57	429.66	664.28
Average daily maximum concentration [mg/L]	Baseline	2.46	1.58	1.75	34.28	34.79	31.62	6.4	4.78	5.35
	RTC	**2.42**	1.45	1.75	**33.52**	32.72	**30.62**	**6.1**	4.31	5.32
	RTC w/ Ensemble	2.47	**1.44**	**1.69**	33.62	**32.65**	**30.36**	6.24	**4.29**	**5.12**
Average daily maximum load [kg/d]	Baseline	841.78	216.61	387.3	8457.74	4754.41	6414.76	1897.82	655.93	1177.53
	RTC	**811.38**	154.86	378.36	**7630.67**	3534.21	6029.99	**1715.96**	458.82	1147.62
	RTC w/ Ensemble	840.77	**153.73**	**335.01**	7848.81	**3493.46**	**5568.27**	1795.79	**455.77**	**1011.62**