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Assessing the Viability of Heuristic Predictive Control for Integrated Urban Drainage Systems

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Abstract

The implementation of real time control (RTC) in integrated urban drainage systems (IUDS) has been extensively explored in numerous studies, with the purpose of improving its performance, particularly, during storm occurrences. This approach frequently focuses on volume-based control, to minimize combined sewer overflows (CSOs) volume and investment costs in CSO controlling and new infrastructures intended to manage these incidents and mitigate polluted discharges into the receiving watercourses. Among the different RTC strategies, heuristic and optimization-based control can be distinguished from the research work available, such as rule-based RTC (RB-RTC) and model predictive control (MPC), respectively. To enhance the viability of RTC, rainfall forecasting has been introduced in the IUDS, to assess the possible combination with RTC and the benefits and risks that derive from it, considering these forecasts are associated with uncertainties. Despite the reasonable results obtained for both control strategies in CSO controlling, only optimization-based control has been combined with rainfall forecasts.

This dissertation assesses the potential of heuristic predictive control in IUDS, by combining RB-RTC with real radar rainfall forecast and applying it to a case study in the Netherlands. An existent full-integrated catchment model built for the IUDS selected for this study was used and sufficiently calibrated to deliver reasonable results compared with monitoring data. The accuracy of the real radar rainfall forecast was evaluated and, when compared with observed rainfall data, it correctly predicts a considerable amount of storm occurrences. One of the two heuristic control strategies developed proved to be beneficial for the performance of the IUDS, contributing for CSO volume reduction and avoiding the overcharge of the wastewater treatment plant (WWTP). This can potentially increase the quality of the receiving watercourses, prevent urban flooding and maximize the efficiency of the WWTP operation. Finally, recommendations, to further improve and explore heuristic predictive control, are provided.

Keywords: Real Time Control (RTC); Rule-based RTC (RB-RTC); Rainfall forecasting; Combined Sewer Overflow (CSO); Integrated Urban Drainage Systems (IUDS)

Resumo

A implementação de controlo em tempo real (RTC) nos sistemas de drenagem urbanos integrados (IUDS) tem sido investigada com o propósito de melhorar o seu desempenho, particularmente, durante eventos de precipitação. Esta abordagem baseia-se maioritariamente na minimização do volume das descargas de emergência (CSOs) e dos custos de investimento no controlo de CSO e em novas infraestruturas projetadas para mitigar estas ocorrências e a deterioração dos emissários. As estratégias de RTC podem ser fundamentalmente baseadas em controlo heurístico e de otimização, distinguindo-se o RTC baseado em regras (RB-RTC) e modelo de controlo preditivo (MPC), respetivamente. Embora esteja associada a incertezas, a previsão de precipitação foi introduzida em IUDS para investigar a sua combinação com o RTC, nomeadamente os benefícios e os riscos. Estas estratégias apresentam resultados razoáveis relativamente ao controlo de CSO, mas, apenas as de otimização foram aplicadas com previsões.

Esta dissertação avalia o potencial do controlo preditivo heurístico em IUDS, através da aplicação de RB-RTC com previsão de precipitação por radar num estudo de caso nos Países Baixos. Para isso, um modelo de drenagem urbana desenvolvido para o IUDS selecionado para este estudo foi utilizado e suficientemente calibrado para produzir resultados razoáveis, comparativamente a medições de monitorização. A precisão da previsão também foi avaliada e comparada com medições, e a mesma prevê corretamente um número considerável de eventos de precipitação. Uma das duas estratégias de controlo heurístico desenvolvidas demonstrou constituir um benefício para um melhor desempenho dos IUDS, uma vez que contribui para a redução do volume de CSO e evita a sobrecarga da estação de tratamento de águas residuais (WWTP). Esta estratégia pode também contribuir para um aumento da qualidade dos emissários, prevenir inundações urbanas e maximizar a eficiência da operação das WWTP. Por fim, são disponibilizadas recomendações para investigar e melhorar o controlo preditivo heurístico.

Palavras-Chave: Controlo em Tempo Real (RTC); RTC baseado em regras (RB-RTC); Previsão de Precipitação; Descargas de Emergência (CSO); Sistemas de Drenagem Urbanos Integrados (IUDS)

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List of abbreviations

BOD_5	Biochemical Oxygen Demand
CS	Control Station
CSO	Combined Sewer Overflow
CSS	Combined Sewer System
DO	Dissolved Oxygen
DWF	Dry Weather Flow
FAR	False Alarm Ratio
FD	Filling Degree
FLC	Fuzzy-logic control
GOC	Global Optimal Control
IUDS	Integrated Urban Drainage Systems
KNMI	Royal Netherlands Meteorological Institute
K-S	Kolmogorov–Smirnov
MPC	Model Predictive Control
NH_4	Ammonium
NSE	Nash-Sutcliffe Efficiency
NWP	Numerical Weather Prediction
PC	Primary Clarifier
PF	Perfect Forecast
POD	Probability of Detection
POFD	Probability of False Detection
PS	Pumping Station
RBC	Rule-based control
RB-RTC	Rule-based Real Time Control
RF	Real Forecast
RTC	Real Time Control
SC	Secondary Clarifier
SSS	Separated Sewer System
SST	Storm Settling Tank
TSS	Total Suspended Solids
UDS	Urban Drainage Systems
UV-VIS	Ultra Violet-Visible Spectroscopy
UWWTD	Urban Waste Water Treatment Directive
WFD	Water Framework Directive
WWF	Wet Weather Flow
WWTP	Wastewater Treatment Plant

1. Introduction

This Chapter briefly explores the history of urban drainage systems, focusing on its concept evolution and the approaches developed to improve its performance and sustainability. However, these approaches can potentially increase the environmental impacts on the receiving watercourses. For this, a modelling tool designed for real time control of the systems is described and its requirements and applications are summarized. The influence of radar rainfall data on the model derived results is also assessed. Finally, the aims and objectives of this dissertation are presented, followed by the outline.

1.1. Urban Drainage Systems

1.1.1. Concept evolution

The main objectives of historic urban drainage systems (UDS) were to collect the stormwater, prevent nuisance flooding and convey wastes. However, since the management of sanitary waste was seen as less relevant, it was essentially handled on-site in cesspools or privy vaults and later transported to a suitable location (e.g., farm, dump outside the city). Besides, the communities also lacked concern or interest for the drainage practices, unless there was a risk of flooding or nuisance conditions in their own neighbourhood (Burian and Edwards, 2002).

In the nineteenth century, the concern for public health safety increased throughout European cities, the United States, and other locations as cholera outbreaks became a major global scourge in over 50 countries. As a result of extensive investigations, it was determined that this epidemic and other bacterial, viral and parasitic diseases (e.g., typhoid fever, hepatitis A) were caused by pathogens transmitted via water supplies that had been contaminated due to the infiltration from cesspools and similar structures (De Feo et al., 2014; Phelps et al., 2017; Tulchinsky, 2018).

Additionally, the inexistence of a proper wastewater treatment process affected not only public health, but also the environment itself, regarding, the pollution of the watercourses and the risk for the aquatic ecosystems. From the end of the nineteenth century, several kilometers of the Seine River (downstream of Paris) were affected by a low oxygen concentration, due to wastewater spills directly into the river. This degradation of water quality has contributed significantly to the decline of migratory fish and even the gradual extinction of several species (Meybeck et al., 2018; Belliard et al., 2020).

The improvement of drinking water quality and the treatment of wastewater became critical issues to solve, to minimize illness and death, caused by contaminated drinking water, and environmental impacts, induced by untreated wastewater discharges. Consequently, during the first half of the twentieth century, the perspective of urban drainage evolved due to the emergence of regulations, monitoring, computer modelling and environmental concerns.

This increased the relevance of ecosystem protection and urban sustainability along with public health and flooding concerns. Moreover, it was during the second half of the twentieth century that Europe, the United States and other locations promulgated regulatory elements addressing urban drainage issues (Burian and Edwards, 2002).

Considering the European legislation, there are two important directives: the Urban Waste Water Treatment Directive 91/271/EEC (UWWTD) and the Water Framework Directive 2000/60/EC (WFD).

The UWWTD (EC, 1991) states that the collecting systems design, construction and maintenance shall be undertaken in accordance with limiting the quantity of pollution of receiving waters due to stormwater overflows. Additionally, this Directive requires reporting of wastewater sewerage treatment performance and a system of preauthorization for all wastewater discharges (EurEau, 2016; Botturi et al., 2020).

The European WFD (EC, 2000) is the key policy driver in the water sector and its main objective is to establish management strategies for improving water quality and protection of the receiving watercourses from wastewater effluent discharges. For this, the collection and management of wastewater and stormwater are essential services for protecting public health and the environment. This Directive aims at the control of diffuse pollution to enable good ecological status in all waterbodies of member states. Moreover, countries also derive national regulations from it to contribute for a sustainable environmental protection and a better management of the urban drainage systems (Botturi et al., 2020).

Urban drainage systems are now viewed as a vital component of a sustainable urban system and developed with the purpose to collect two main inflows: urban- and industrial wastewater and stormwater. To process these inflows, there are two conventional designs of an urban drainage system, namely, a combined sewer system (CSS) and a separated sewer system (SSS). A CSS collects and transports both inflows to a wastewater treatment plant (WWTP) before discharging the treated water into the receiving waters. While a SSS carries the wastewater and the stormwater in separate pipes and only the former is submitted to a complete treatment before being discharged (De Feo et al., 2014). The latter approach is more expensive, due to the construction of two separate pipe networks, but still allows a reduction of the hydraulic capacity of the WWTP.

Although both designs have their advantages, a storm event often poses a threat, as it can lead to the flooding of the urban area and increase the pollution of the receiving water bodies. In fact, stormwater discharges through SSS not only influence physicochemical variables, such as pH, total suspended solids (TSS) or biochemical oxygen demand (BOD_5), of the receiving waters, but also have an impact on organisms living in the water column and in the bottom sediments (Rossi et al., 2013; Baralkiewicz et al., 2014). The WWTP is designed to operate and treat a certain amount of wastewater volume and flow rate, and, even applying a factor of safety, heavy storm events can still increase the inflow to the collection system and the flow rate.

This can potentially overload and impair the performance of the WWTP (Droste, 1997; Tchobanoglous et al., 2003; McMahan, 2006).

To reduce the risk of flooding, emergency overflows, namely combined sewer overflows (CSOs) were introduced in the CSS as a new and cost-effective approach to manage high flows during heavy storm events.

1.1.2. Combined Sewer Overflow (CSO)

A CSO receives an inflow that comprises a mixture of untreated raw sewage and stormwater and divide it into two outflows, one continuing its path to the WWTP and one to the receiving water (Figure 1.1). Its objective is to prevent the potential urban flooding and an overcharge of the WWTP and to alleviate any flows beyond the capacity of the network (Bailey et al., 2016; Butler et al., 2018).

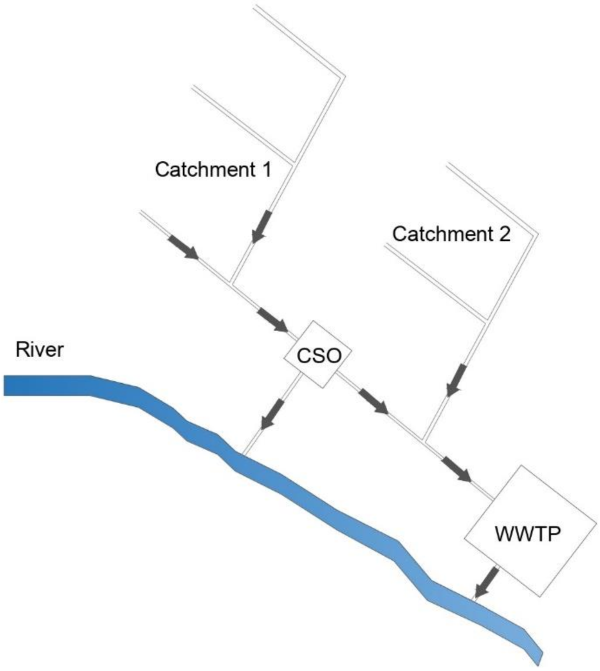

Figure 1.1 - Simplified layout of a combined sewer system (adapted from Butler et al., 2018).

The CSO is a weir, and whenever the surface of the flow passing through is below its crest, the flow continues to the WWTP only. When the water level increases and its surface is above the weir crest, then some of the flow passes over it, while the rest continues to the WWTP (Butler et al., 2018).

Since CSSs are usually unable to manage the flows experienced during heavy storm events, these infrastructures function as a relief mechanism and an overall good solution for the urban drainage system. For this reason, the European Federation of National Associations of Water Services, EurEau (2016), has estimated that there are 2.2 million km of existing sewerage systems in Europe, of which approximately 70% of the total network corresponds to CSSs.

Consequently, there are approximately 650 000 CSOs and their impact on the receiving watercourse is an increasing concern across the European countries. In the Netherlands, around 68% of the system network is mainly CSSs, where a total of 13 700 overflow structures were reported in 2013. This number of structures can be explained by the existence of smaller systems and short transport distances due to the presence of high groundwater tables in the soft and flat soils of this country (Cools et al., 2016). CSOs occur five to ten times a year per location in this country (Scherrenberg, 2006).

Since CSOs contain raw sewage blended with large volumes of stormwater, it can lead to the release of pathogens, solids, debris and toxic pollutants into the receiving waters, which creates serious public health and water quality concerns. For instance, CSOs have contributed to beach closures, shellfish bed closures, contamination of drinking water supplies and other environmental and public health impacts (US EPA., 2004). Even though these discharges are mainly produced by storm events, incidents such as blockages within the chamber of the asset are still possible, resulting in the asset discharging during dry weather and increasing the pollution of the receiving watercourse (Bailey et al., 2016).

1.1.3. CSO Impacts

Intermittent discharges from CSOs can lead to impacts on the receiving water bodies. These impacts can be divided into direct water quality effects, such as dissolved oxygen (DO) depletion, increase of nutrient concentrations and toxic substances, and public health issues.

Concerning the direct water quality effects, DO depletion is the one of the major concerns, since low levels of oxygen in the receiving waters can be harmful, and, even, fatal to the aquatic systems, resulting in the reduction of biologic diversity. This phenomenon is mainly caused by intermittent discharges due to the mixing of low DO spills with the receiving water and the increase of organic content, which leads to the immediate oxygen demand for the biodegradation of discharged (dissolved or particulate) organic matter (Angerville et al., 2013; Botturi et al., 2020). However, the introduction of excessive quantities of nutrients (e.g., nitrogen and phosphorus) can also contribute to this depletion, due to the rapid growth of algae and nuisance plants and, consequent, eutrophication (US EPA., 2004). Additionally, other CSOs effects include the introduction of toxic substances (e.g., ammonium, heavy metals, microcontaminants) and the alteration of physical parameters (e.g., temperature, suspended solids, flow, pH) in the receiving water bodies (Gasperi et al., 2008).

Regarding public health issues, these overflows are expected to have relatively high concentrations of a variety of pathogens (i.e., fecal coliform, *E.coli*, enterococcus bacteria) originated from human faeces and organic waste in the sewage, which constitutes a risk for public safety (Wang, 2014). Consequently, if the receiving waters are used for recreational purposes, these microbial contaminations can increase the risk of infections leading to gastrointestinal and respiratory illnesses (McBride et al., 2013; Riechel et al., 2019).

European countries have identified CSOs as an important issue and national standards have been established with the purpose of regulating stormwater overflows. In general, approaches in standards and guidance mainly focus on a limit on the number of overflows (e.g., Netherlands, Portugal), requirements for dilution (e.g., Bulgaria) and others, particularly, max total volume or max number of days of overflows (e.g., Germany). Additionally, the permitted number of overflows per year proposed by CSO regulation guidelines differs according to each member country, for example it can range from 2 to 3 in the Netherlands (EurEau, 2016; Botturi et al., 2020).

Since CSO structures are not designed for monitoring purposes, it becomes challenging to determine if these objectives are achieved. There are various methods to estimate CSO volumes, as proposed in literature (Maté Marín et al., 2018), and measurement devices (i.e., sensors and probes) are also applied for monitoring purposes in most of the high-income countries. These devices (e.g., conductivity meters, level sensors, UV-VIS) allow to determine CSO occurrence and duration, water level, and, even, water quality (Montserrat et al., 2013; Brzezińska et al., 2016). However, location, communication, operation, maintenance and recalibration of these devices are some of the factors that still hinder CSO monitoring, thus a direct measurement of emission flow rates at the weir is nearly impossible with the current available sensor technology (Gruber et al., 2005; Rasmussen et al., 2008; Hofer et al., 2014). For this reason, to assess potential flooding and pollution incidents, it is important to focus on real time monitoring of flow rates and effluent levels of the system's network, and not just the CSOs. The main objectives of this monitoring consist in supporting decision making in real time or quasi-real time about actions to be taken, evaluating the performance of the system and calibrating the urban drainage models used (Ahm et al., 2016; Botturi et al., 2020).

There are different strategies developed to mitigate the impacts and achieve the requirements of the relevant regulations of CSOs, such as increasing storage capacity, detention/ retention facilities and sewer separation. However, these options can be prohibitive due to cost and not always guarantee pollution reduction (Li et al., 2010). Real time control systems seem a cost-effective alternative to reduce the impacts of CSOs since they only require additional implementations to the existing systems (Colas et al., 2004).

1.2. Real Time Control (RTC)

Real Time Control (RTC) is a tool that utilizes real time hydraulic information of the urban drainage system and allows the adjustment of the flow in real time (Schütze et al., 2004). As van Daal-Rombouts (2017) mentions, in terminology, it can be seen as a control algorithm that sets the system actuators (for wastewater systems e.g., pumps, valves, movable weirs, etc.) to their optimal values based on real time input from process variables (water levels, flow capacities, rainfall, etc.) that reflect the current systems functioning.

Regarding its application, there are some aspects to consider when approaching this tool. First of all, RTC has several requirements that need to be fulfilled, such as:

- A goal for the functioning of the system should be determined;
- Existence of actuators in the system is preferable;
- The systems functioning with respect to the goal should be sensitive for actuator operation;
- Real time measurements representative for the systems functioning should be available. These measurements are provided by sensors, such as rain, water level, flow and quality gauges.
- A communication system to transfer measurements and actuator settings has to be operational;
- A model describing the systems functioning should be available for the design, and possibly implementation, of the control algorithm.
  (Schütze et al., 2003; Schütze et al., 2004; van Daal-Rombouts, 2017)

Considering these requirements, the applications can range from a very basic local control (Figure 1.2A) to a global control (Figure 1.2B).

When the actuators are not remotely operated from a control room and if process measurements are taken directly at the actuator location, then the system is operated on a local control (e.g., switching a sewer pump based on a water level measurement in a pump sump). If the system is more complex or all the actuators have to be operated collectively, the outcome is named global control. In this case, a central control room receives all the measurement data of local sensors and centrally operates the actuators in a coordinated way. For instance, the adjustment of WWTP influent capacities on anticipate flows based on rainfall measurements in a contributing catchment (Schütze et al., 2004). Besides these two centralized applications, there is also decentralized control that focuses on measurements at a particular location that are transmitted to the local actuator and neighbouring actuators, which communicate, interact and plan their control actions autonomously (Figure 1.2C). Garofalo et al. (2017) proposed an urban drainage network equipped by sensors and a series of electronically movable gates controlled by decentralized real time system. This decentralization consisted in the perception of the water level by a sensor located at a specific gate, that communicated with neighbouring gates to elaborate a proper actuation strategy for its gate.

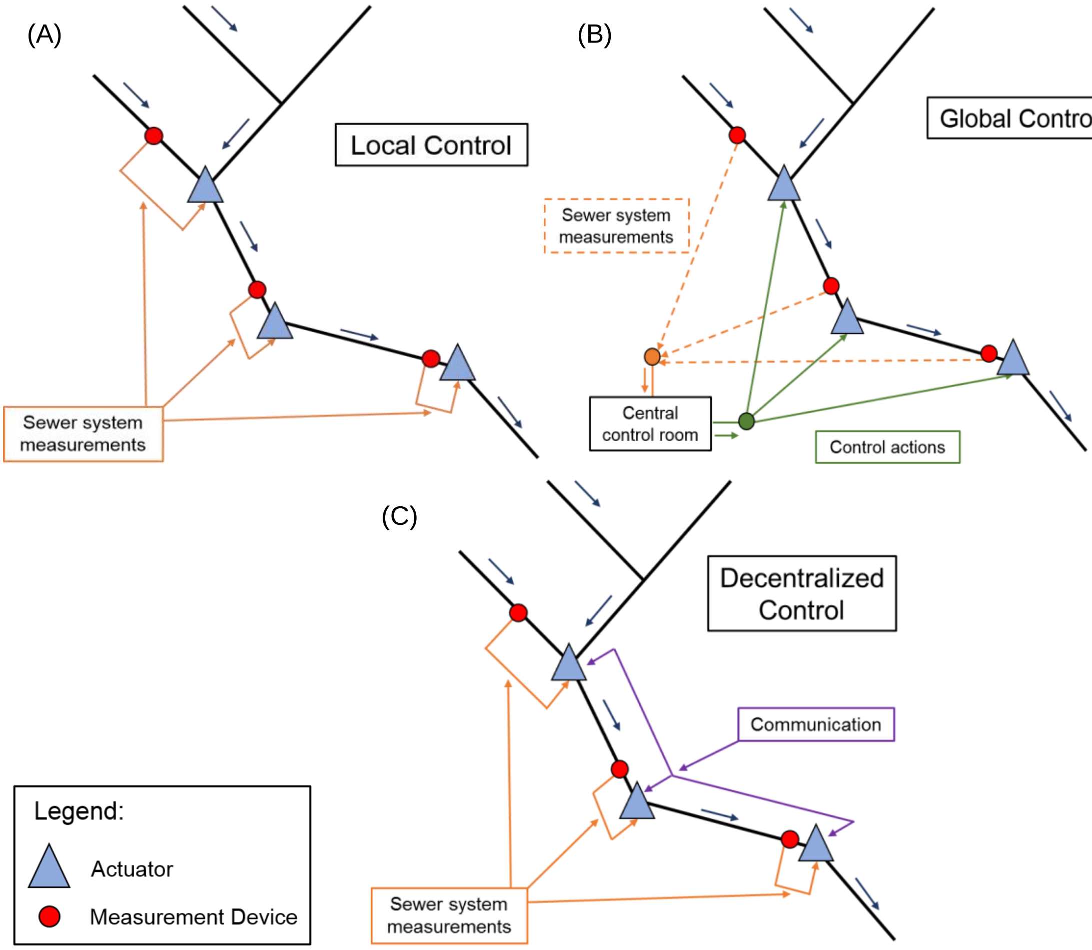

Figure 1.2 – Simplified layout of local, global and decentralized control in a sewer system.

The objectives set for these controls can be achieved through heuristic algorithms and optimization-based algorithms (García et al., 2015).

A heuristic algorithm is based on experience or knowledge already acquired, and it is especially developed to have low complexity and to be used for systems that prove a considerable complexity for modelling. While this algorithm does not require a control-oriented model of the system, there is still a need to use simulation-oriented models of the urban drainage system to evaluate the performance of these controllers and allow further improvement. Rule-based control (RBC) and fuzzy-logic control (FLC) are the most common heuristic algorithms (García et al., 2015).

Optimization-based algorithms usually deal with the problem of generating control strategies with the objective of minimizing or maximizing certain criteria, seeking the optimal control action based on the measures (or estimations) of current system variables. There are numerous examples of these algorithms, including linear-quadratic regulator (LQR), evolutionary strategies (EA), and population dynamics-based control (PD) (Branke et al., 2008; García et al., 2015).

Model predictive control (MPC) for combined sewer systems is not an algorithm but rather an optimization-based control, defined as a set of control methodologies that use a mathematical model of the system to compute the control actions required to minimize a cost function. In addition, it is considered an adaptive control strategy, since the optimal control is recalculated consecutively as new information about the current state of the sewer system and new rainfall forecasts become available (Ocampo-Martinez, 2010; Lund et al., 2018). An overview of this topic is available in Lund et al., 2018.

Considering control strategies, RTC can be divided into three different types: volume-based, pollution-based and impact-based.

Volume-based RTC is a control strategy that consists in minimizing the volume of polluted water entering the receiving water by storing or treating it. This strategy can reduce the frequency and volume of CSO events, and it is a simple and robust approach. Due to its simplicity, it is not considered the optimal solution to reduce the quantity of pollutants discharged in the receiving waters (Weyand, 2002; Pleau et al., 2005; Dirckx et al., 2011a).

Pollution-based RTC accounts for the quality of these CSO discharges and it is designed to minimize the total amount of pollutants entering the receiving water by preferably storing polluted water and spilling more diluted water. This can allow to determine the pollutant load in the wastewater and prioritize the access of the more polluted wastewater to the WWTP, up to the limit of available hydraulic capacity. For this strategy, additional quality measurements of the wastewater are required which can be difficult to obtain or subject to uncertainties (Lacour et al., 2011; Vezzaro et al., 2014).

Impact-based RTC tries to minimize the impact of the UDS on the receiving water quality directly, meaning the sensors in the receiving water are used to manipulate pumps and weirs in the sewer system, treatment plant and/or receiving water (Risholt et al., 2002; Erbe and Schütze, 2005). This type of strategy demands a certain knowledge of the dynamics, not only the sewer network, but also about the WWTP and the receiving waters. The concentration of a particular parameter (e.g., ammonia) in the receiving water can be improved, due to the increase of polluted water going through the biological treatment at the WWTP (Vanrolleghem et al., 2005). The measurements obtained for these parameters can also be subject to uncertainties. Additionally, any of the three strategies mentioned require information on water quantities, such as water level measurements and possibly flows.

1.3. Relevance of Radar Rainfall Data

Stormwater is the major cause of overflows and CSO discharges of the UDS, which increases the pollution of the receiving water bodies. Therefore, the development of methods to represent and predict rainfall can become advantageous in the design, analysis and operation of drainage systems (Butler et al., 2018).

Based on literature (Willems, 2001; Thorndahl et al., 2008; Schellart et al., 2012; Moreno-Rodenas et al., 2019), rainfall input data errors correspond to one of the most important sources of uncertainty in urban hydrological models. In addition, for extreme events, uncertainties related to spatial variability and rainfall measurement errors can increase (e.g., Berne et al., 2004; Hossain et al., 2004; Brauer et al., 2016).

Radar rainfall data becomes a fit choice for urban hydrological modelling, as its main strength for rainfall estimation corresponds to their capability of providing spatially distributed rainfall information and enabling forecasting with a lead time of a few hours. Nonetheless, radar rainfall data still suffers from uncertainties (Verworn and Krämer, 2005; Thorndahl et al., 2017).

To reduce uncertainty and provide the best possible rainfall estimates for historical records or in real time, the majority of national meteorological services are capable of producing radar rainfall products, which have been adjusted or merged with rain gauge network data. Hydrological model simulations (offline mode) can benefit from the use of these rainfall estimates, as there is not a need for continuous adjustment of radar rainfall against rain gauges and only historical data is required (Thorndahl et al., 2017).

On the other hand, urban hydrological model outputs can also be subject to uncertainties in the estimation of hydrological and hydraulic processes due to parameter uncertainty (e.g., Thorndahl and Willems, 2008; Thorndahl et al., 2008; Dotto et al., 2012). If these uncertainties are high, it becomes more relevant to calibrate or optimize directly the hydrological models to match runoff response observations (Thorndahl and Rasmussen, 2013; Löwe et al., 2014).

The introduction of urban rainfall forecasts, particularly, short-term forecasts or nowcasts, in real time prediction of sewer system states has become an interesting approach in providing input for real time warning and/or control of urban floods or CSO discharges. These inputs are called nowcasts due to their limited lead times, varying from 30 min to 2h (Achleitner et al., 2009; Foresti et al., 2016).

Numerous model-based real time control methods have been developed for applications with online in-sewer instrumentation or rain gauges for local systems (e.g., Schütze et al., 2004) and, with progress in estimating spatially distributed rainfall with radars, the implementation of real time control on a larger scale (e.g., a whole city) became a possibility. To mitigate spills, overflows and/or flooding, new methods were developed to exploit spatial variability of rain and successive unequal local loading of the hydrological systems and focus in utilizing the spare capacity of these systems (e.g., Faure and Auchet, 1999; Mounce et al., 2014). Others have been used to estimate the loads on WWTP with the purpose of reducing spills of untreated waste and stormwater and optimizing the treatment processes during rain (Fuchs and Beeneken, 2005; Thorndahl et al., 2013; Vezzaro and Grum, 2014; Kroll et al., 2016). Regarding certain developments, such as large linked hydrological systems, centralization of treatment plants in urban areas and advances in model predictions and data, there seems to be a large potential for global predictive control of hydrological systems in cities, which has not been fully exploited yet (Thorndahl et al., 2017).

1.4. Aims and Objectives

As described in the previous subchapter, the research accomplished, so far, allows the opportunity of assessing the potential use of rainfall forecast in real time control. In Chapter 2, the literature review performed leads to the following main research question:

> *Can the use of rainfall forecast enhance heuristic control in integrated urban drainage systems (IUDS)?*

The main question presented above can be specified in four sub questions:

- Is it possible for an IUDS model to deliver accurate results?
- How accurate is the radar rainfall forecast data compared with observed rainfall data?
- What are the benefits of the control implemented?
- What are the risks of the implementation?

This project combines theoretical work on the available instruments and a methodology for the implementation of radar rainfall forecast in RTC with a practical application of this methodology on a case study.

1.5. Outline

This thesis follows the research questions defined in the previous subchapter. Chapter 2 focuses on reviewing literature and research work that analyses the potential use of radar rainfall data and nowcasts in real time operation of urban drainage systems.

In Chapter 3, a methodology is proposed to assess the main research question and the case study is presented. Accordingly, the results obtained with the application of the proposed methodology are presented and discussed in Chapter 4. Moreover, the four sub questions are also dealt in this chapter.

Finally, Chapter 5 reaches the answer to the main research question, providing conclusions about the topic, and Chapter 6 presents recommendations for further research.

2. Literature Review

2.1. Introduction

This Chapter aims at providing the relevant studies that led to the main research question and sub questions presented in subchapter 1.4. First, in subchapter 2.2, an overview of the RTC application is described to understand its benefits in urban drainage systems, which includes studies that evaluated its performance based on CSO volume reduction, receiving watercourse impacts and investment cost savings. In subchapter 2.3, three RTC strategies are analyzed and compared through different studies. Subchapter 2.4 deals with use of rainfall data, particularly rainfall forecast, in RTC to assess previous research work with similar objectives, as the ones presented in subchapter 1.4. The combination of the literature described in these two subchapters generated the main research question of this dissertation. Finally, in subchapter 2.5, a summary of the main points found in this literature review is presented, justifying the purpose of this project in the response of the main research question and sub questions formulated.

2.2. Overview of RTC application

Before implementing real time control in an urban drainage system, its benefits and costs need to be determined and analyzed to either support or oppose its application in a particular case. For this reason, performance indicators are defined to evaluate the performance of the followed approach. In general, the selected indicators are CSO or overflow volumes and/or frequencies but preventing flooding and equalizing peak discharges towards the WWTP can also be another objective (Schütze et al., 2004).

Entem et al. (1998) reported the results of a European project that focused on the implementation of real time sewer system control for eight European cities and determined a reasonable performance in the mitigation of overflow events in the system, considering prediction and generation of strategies. Besides, other researchers, such as Carbone et al. (2014), also investigated the use of RTC in urban drainage systems, as an innovative alternative to optimize the storage capacity of the network during storm events.

The implementation of RTC in practical applications not only can be beneficial in volume-based issues but can also contribute to the reduction of costs, since it can improve the performance of the existing system and avoid unnecessary investments in CSO controlling and new infrastructures (Schütze et al., 2004).

Colas et al. (2004) evaluated the benefits in applying real time control on CSOs for four different cities and types of events. When comparing the sewer systems without and with RTC, the following results for CSO volume reduction (in %) and investment cost savings (in €) were obtained for each case study (Table 2.1).

Table 2.1 - CSO volume reduction and expected cost savings from RTC in four cities (Colas et al., 2004).

Cities	CSO volume reduction (%)	Investment cost saving (€)
Paris, Île-de-France	24 - 100	899 618 500
Louisville, Kentucky	52 - 87	122 675 250
Quebec City, Quebec	23 - 46	73 605 150
Wilmington, Delaware	32 - 63	98 173 800

Similarly, in terms of mitigating CSO volume and its impacts at the lowest cost, Dirckx et al. (2011a) compared the use of static solutions (i.e., disconnection of sealed surface, building of storage tanks and the adjustment of throttle structures) with RTC. To assess that comparison, a local representative catchment (Kessel-Lo in Flanders/ Belgium) was used, and the simulations were carried out in a verified and recent hydrodynamic sewer model (Table 2.2).

Table 2.2 - CSO volume reduction and investment cost results (Dirckx et al., 2011a).

CSO mitigation approach	CSO volume reduction (%)	Investment cost (€)
Disconnection of sealed surface	45 - 90	22 750 000 - 68 250 000
Building of storage tanks	90	5 700 000 - 13 100 000
Adjustment of throttle structures	25	137 000 - 274 000
RTC	20 - 65	69 000 - 303 000

As it can be observed in the previous table, storage tanks seem to be the most efficient solution for minimizing the overflow volume, in this case study. However, RTC is cheaper than disconnection and storage tanks and only marginally more expensive than throttle adjustment. Therefore, in terms of highest overflow volume reduction versus annual equivalent cost, RTC proves to be the best cost-effective measure for this particular case study. In addition, RTC has the capability of adapting to new situations and allowing preferential spilling into more robust watercourses, which turns it into a remarkable reduction strategy, especially, if combined with reduced storage tanks (Dirckx et al., 2011a). Both researchers demonstrate an advantageous performance from RTC in various case studies, in terms of cost and CSO volume reduction, but the results cannot be generalized, as this tool can work differently for each urban drainage system and strategy applied.

Bachmann-Machnik et al. (2021) studied the use of highly resolved online flow and quality monitoring data to optimize static outflow settings of CSO tanks and compared it with RTC strategies for CSO emission reduction. The methodology was developed on a conceptual drainage system with two CSO tanks. In this conceptual catchment, optimizing the outflows from the two CSO tanks based on measured data provided reliable results, reducing a major part of the emissions (i.e., up to 17%) to the receiving water body.

Compared to the static outflow settings, the additional benefit of RTC was low (i.e., a maximum of 3%), which is considered a theoretical potential in this study. This is not achievable, due to flow times between tanks and the hydraulic capacity of the connected sewer network, meaning the real control potential could be even lower. The reason for this value could be the small study area, comprised of only two CSO tanks, meaning that larger catchment areas could possibly increase the RTC CSO reduction potential.

Langeveld et al. (2013) investigated the potential for impact-based real time control for the improvement of the Dommel river (Eindhoven, The Netherlands) water quality, using an integrated model for the urban drainage system. Four heuristic RTC strategies (i.e., rule-based RTC) were implemented in the model and were compared using two main performance indicators, namely ammonium (NH_4) and dissolved oxygen (DO) concentrations in the closing river section. The analysis of the RTC strategies developed led to the conclusion that RTC can increase the system's performance and the receiving water quality compared with its current operation. However, this tool was considered insufficient without additional measures to achieve the water quality requirements for NH_4 and DO. Based on the results obtained, the researchers stated that weather forecasts (e.g., short-term radar or nowcasting) should be incorporated in the development of the control and decision support systems but that the quality of these forecasts still required further improvement. Additionally, it is probable that the simplicity of rule-based control hindered the performance of the strategies applied, thus further assessment is essential.

2.3. Comparison of RTC strategies

Rule-based RTC (RB-RTC) is considered one of the simplest heuristic RTC strategies and it consists in the development of a script of rules (mainly if-then rules) that control the system, depending on its conditions and current state. An example of this is the regulation of the water level in the storage tank, so if the water level increases and surpasses an established threshold, then through the system actuators, only an amount of discharge to the drainage system is allowed to prevent or mitigate an overflow. The simplicity of this RTC strategy can be seen as an advantage but, also, a disadvantage. Even though the rules established can be derived from standard evolutionary algorithms or other established frameworks, the expertise and knowledge of the rule developer is generally applied. If a system is larger and more complex, more rules are necessary to control the system (García et al., 2015).

Nielsen et al. (2010) designed and tested an RB-RTC strategy to improve the performance of a combined sewer system in the city of Kolding (Denmark) and reduce CSO emissions to the Kolding River and estuary. This RTC strategy was applied in a full hydrodynamic model setup on 9 pumping stations and gates were installed in 7 detention basins. The control rules implemented were based on the total inflow to the WWTP and water levels in the basins and in critical parts of the systems. To evaluate the performance of the RTC system, the reduction of CSO volume was calculated using storm events over the last 10 years. The results showed that RB-RTC had the potential to reduce up to 40% of the discharge volumes to Kolding River, compared with the reference scenario (no RTC). This study also indicated that these results correspond to the absolute minimum for the control potential and that further optimization could possibly be achieved by implementing rainfall forecasting.

Mollerup et al. (2013) evaluated the use of RB-RTC in Copenhagen's sewer system for a period of sixteen years to understand if this approach could adapt to the evolution of regulation and climate factors. During this period, along with the new additions to the system (e.g., retention basins), RB-RTC could still contribute to a CSO volume reduction and remained an intuitive way of controlling the system. However, it was also stated that this control is limited because it focuses on local control of the actuators involved and struggles to retain its effectiveness against heterogeneously rainfall distribution over the catchments.

Another heuristic alternative is fuzzy-logic control which uses a set of simple rules as well but combines it with a flexible specification of output parameters. While conventional controllers require a set of differential equations that represent a model of a dynamical system to adjust the control sizes of the system, fuzzy control obtains control values on the basis of fuzzy rules, which are similar to the model of human reasoning (Abdel-Aal et al., 2016).

Seggelke et al. (2013) studied the performance of a fuzzy based RTC strategy in an urban drainage system in Wilhelmshaven (Germany), which one of the objectives was reducing the volume and number of overflows at a particular CSO, located close to a bathing beach. The other main objective was to avoid critical situations in the operation of the WWTP during storm events, thus the strategy combined the control of the sewer network and the inflow to the treatment plant. During single CSO events, the simulation studies suggested a reduction of CSO volume, of approximately 40%, at one of the pumping stations. However, controlling the discharges from this pumping station for the whole year only resulted in a CSO frequency and volume reduction of 23% and 25%, respectively. This discrepancy was possibly caused by a smaller impact of the diversion to the other sub-catchment than expected and by a different system behaviour than assumed in the simulations. It was also verified that WWTP could be protected from critical situations without increasing significantly the CSO volumes.

Ostojin et al. (2017) presented a control system, named CENTAUR, that utilizes a FLC strategy with the goal of regulating the water level at the flooding site and minimizing the risk of localized flooding through a flow control device. In September of 2017, this control system was implemented and fully functional in a trial site, located in Coimbra (Portugal). An amount of three storm events was selected to test the performance of CENTAUR system and compare it to a model simulation without it. During those events, CENTAUR allowed a 28% reduction of the peak water levels, proving to be beneficial for flood protection. Moreover, FLC strategies have been used in several other wastewater system applications (Ostojin et al., 2011; Shepherd et al., 2017).

When comparing these two heuristic approaches, Klepiszewski and Schmitt (2002) investigated the efficiency of these RTC strategies in reducing CSO volume and verified that both RB-RTC and FLC can similarly meet the objective of the preconditioned control strategy. However, the procedure of FLC is more complex to establish than the procedure of RB-RTC, and compared to it, an improvement of RB-RTC processes requires a change of single rules or adding of new rules to the rule base. Although, more investigation has to be performed, it is conclusive that the functioning of RB-RTC processes is more comprehensive, and effects of changes in the control system are more predictable for technical staff than in a FLC process, making it seemingly a more effective control system.

Both approaches seem appealing, but these can struggle to obtain an optimal solution and to handle numerous sensors and actuators within the sewer network, becoming more complex. A strategy more suited to manage these systems and achieve optimal control is model predictive control (MPC). MPC is defined as a control strategy used in urban drainage systems that predicts the response of these systems, based on new information about its state and rainfall forecasts, and establishes the optimal control action. It is suitable, not only for local, but also global control, as it can handle large and complex urban drainage systems with multiple CSO structures, WWTP and actuators and storage basins (Lund et al., 2018).

Cembrano et al. (2004) tested a global optimal control prototype (MPC) in a case study (i.e., Barcelona's urban drainage system) to mitigate combined sewer overflows and prevent flooding. The control strategies were computed based on rain forecasts for the actuators to produce the best admissible states of the network. The information presented about the rain forecasts is limited, which does not allow to understand if this data was authentic (e.g., provided by a meteorological institute) or extrapolated rainfall estimates generated by the researchers. A comparison between the results of applying optimal control, the use of a new detention reservoir passively (i.e., keeping the inlet and outlet gates open at all times) and the original drainage system were performed. Regarding flood prevention, optimal control improved flood volume reduction by approximately 30%, while passive reservoir control improved it by approximately 26%. This corresponds to a 4% difference in the minimization of flood volume, which is not a significant improvement by the optimal control. The CSO volume minimization for the two control strategies was only below 3%.

Puig et al. (2009) implemented a real time global predictive optimal control in the Riera Blanca catchment (Barcelona sewer network), using a software tool named CORAL (Spanish acronym for Optimal Control of Sewer Networks). The objectives were identical to the previous study, mainly focusing on flooding prevention and CSO reduction. The global control results were compared with those obtained using current local control system and it was verified that global control outperforms simple control, achieving a CSO reduction of 18%. Additionally, both studies aimed at maximizing sewage treatment at the WWTP, to promote flooding prevention and CSO mitigation, which led to an increase of treated effluent during storm events, varying from, approximately, 7% to 50%.

Meneses et al. (2018) compared the use of a global risk-based dynamic optimization strategy (MPC) and a coordinating rule-based RTC strategy (RB-RTC) in a detailed hydrodynamic model for storm events recorded during a five-year period. The aim of the study was to investigate the benefits of these approaches in reducing CSO volumes, environmental impacts and utility costs, in the Lundofte catchment in Denmark. The optimization procedure of the RBC was based on a trial-and-error approach which led to the modification of outflow set-points depending on the filling degree of the local and neighbouring basins and the risk for the most sensitive receiving waters. MPC applied a Dynamic Overflow Risk Assessment (DORA, Vezzaro and Grum., 2014), which combines actual measurements of the system, rainfall-runoff forecasts and the uncertainty of these forecasts to minimize the global risk. In this research, “perfect” rainfall forecasts, which consists in applying forecasting to rainfall measurements, were used to generate runoff volume predictions that correspond to actual inflows to the controlled points, with a lead time of two hours. The results showed that the two strategies promoted the reduction of CSO volume, environmental impacts and utility costs by approximately 10%. This is indicative that the use of MPC is not necessarily better than RB-RTC, since the RB-RTC scenario produced good results and it was simpler and faster to implement than MPC.

Kroll (2019) also compared the costs and benefits of RB-RTC and MPC on the basis of detailed hydrodynamic models for five catchments of the River Nete basin (Flanders, Belgium). The RB-RTC strategies used rely on the concept of filling degree of a storage basin or in-sewer storage with respect to a maximum level, commonly the weir crest level of the lowest CSO or the lowest manhole ground level of the subbasins (including a safety margin). To maximize the use of the storage capacity of the sewer system, the most common approach in RB-RTC to define local setpoints for each basin is by two-point control (“on/off” or “open/close”), using a PID controller, as implemented by Dirckx et al. (2011b). The simulations were carried out using historical rainfall series, but, for the MPC scenarios, perfect rainfall data prediction was also assumed to consider the full theoretical potential of this control technique. When analyzing CSO volume minimization, the best result was found for the larger catchment, with about 50% volume reduction by RTC implementation. However, the results between RB-RTC and MPC scenarios were very similar. This can be explained by the selection of small catchments and straightforward evaluation criteria for this study, which do not require the additional complexity of MPC and results in no further improvement compared with RB-RTC. For larger and more complex catchments, MPC can be expected to generate overall better results than RB-RTC, but more effort should be focused in investigating and comparing these control strategies and their applicability in urban drainage systems.

Having reviewed these control approaches and its impacts on the system, studies have also assessed the simulation of the sewer system, WWTP and receiving waters as integral parts of the urban drainage system and combined it with RTC. An integrated model allows the implementation of an entire IUDS on a single modeling and simulation platform to efficiently simulate and analyze both quantitative and qualitative aspects of the wastewater and control the environmental conditions of the receiving waters. Additionally, this model has a fast simulation speed, and its management is reasonably simple (Schütze et al., 2004).

Benedetti et al. (2009) developed an integrated model of a river basin and of two WWTPs with their sewer systems and drainage catchments to improve the environmental and economic performance of the IUDS. The integrated model was implemented on a single modelling and simulation platform (WEST) and it was used to determine good operational parameter sets (i.e., operational variables and their optimal values) for dry weather conditions and for a storm event. The river's water quality obtained was later compared with the current situation ("individual management"). The operational parameters were identified and optimized, leading to improvements in cost reduction and in the average and peak parameter values in the river. These results can be used to develop the knowledge base of an environmental decision support system to improve the decision-making process and generated rules in the online management of the receiving waters.

The research presented, in this subchapter, allows to conclude that, when compared with other control strategies, RB-RTC simplicity still produces good results and allows for a significant CSO volume reduction. One of the differences between this strategy and MPC is the implementation of predictive control (i.e., the use of rainfall forecasts) in the simulations, which could potentially enhance the performance of volume-based RB-RTC. In terms of assessing and implementing this control in a model, an integrated model is preferable because it allows to reduce model complexity, overcome communication problems between different software platforms and reduce simulation speed compared with detailed models. When maximizing the volume of water going into the WWTP, it is also important to evaluate how the control actions affect the treatment and effluent's quality to protect the receiving water bodies. An integrated model allows to check the treatment plant's efficiency and adjust the control settings for a better use of the existing facilities (Vanrolleghem et al., 2005; Borsányi et al., 2008; Benedetti et al., 2009). Before exploring the application of rainfall forecasts in RTC, it is relevant to assess previous research work that utilized rainfall forecast data to evaluate the benefits and risks that come from it, including its accuracy compared with observed rainfall data.

2.4. Rainfall forecasting

Rainfall forecasting can potentially become a valuable asset when implementing RTC in urban drainage systems. However, research work in this topic has been hindered due to rainfall data uncertainties. Willems (1999) showed that, for a sewer system model in Belgium, around 20% of the total uncertainty in the downstream sewer discharges could be associated with rainfall data, namely, spatial variability. Similarly, Moreno-Rodenas et al. (2019) analyzed dissolved oxygen uncertainties in a large-scale integrated catchment model in the Netherlands and verified that rainfall accounted for roughly 20% of the uncertainty in the model simulations.

Implementing predictive control in integrated modelling using rainfall forecast can be quite challenging due to these data uncertainties, thus it raises the question about what methods could be applied to mitigate it. In the literature, there are some studies available that assess the potential of using radar rainfall data, with or without nowcasting (i.e., short-term forecasts), in real time operation of urban drainage systems.

Yuan et al. (1999) studied the possibility of applying predictive real time control in urban drainage systems, using distributed rainfall data derived from weather radar as model input. This paper presents a case study of an actual UDS with the main objectives of detecting the starting time and duration of sewer spills and predicting the drainage load level and the system spare capacity. The performance of the model used was evaluated by comparing the model prediction outputs with the observed system outputs for five contiguous storm events and, in general, the predicted hydrographs were a close match to the observed hydrographs. Moreover, the authors indicate the situations in the events observed where RTC could have played an important role in the operation strategy. However, this research does not verify the simultaneous implementation of RTC and rainfall forecasting, and the benefits and risks associated with it.

Thorndahl et al. (2013) and Thorndahl and Rasmussen (2013) investigated the potential of using extrapolation-based radar rainfall nowcast as input to an urban drainage model for flow prediction in sewer systems. This purpose was evaluated for the forecasting of the inlet flow to a WWTP and the flow in a small urban catchment used as a case study, respectively. When comparing the observed and modeled hydrographs, it can be concluded that radar rainfall nowcast, with short lead times (i.e., up to two hours), can provide an acceptable performance, in terms of short-term forecasting. However, as the authors mentioned, these studies are meant to demonstrate how flow forecasting could be implemented in real time operation, and not to assess how it could be used in real time control of a drainage system. Therefore, it is unconsidered if the systems evaluated could prevent or mitigate possible CSO or urban flooding in the storm events selected for the studies. Nevertheless, considering a possible combination of urban hydrological forecasting with real time control of drainage systems, the researchers indicate that the purpose would also be to predict when and where the flow or water level would exceed a certain threshold, to utilize the spare capacity of the system. In addition, the radar forecast or nowcast obtained is extrapolation-based and not real radar rainfall forecast data, which can potentially diminish the reliability of the model simulations.

Similarly, Vieux and Bedient (2004), Achleitner et al. (2009), Liguori et al. (2012), Löwe et al. (2014) and Schellart et al. (2014), explore the use of radar rainfall data (also with or without nowcasting) for flow prediction in urban drainage systems. These studies either focus on quantifying prediction uncertainties, minimizing those uncertainties, improving radar rainfall forecasts or evaluating the performance of nowcasts with different lead times.

Vieux and Bedient (2004) verified that the uncertainty in the radar rainfall inputs is significantly reduced if the radar data is corrected or adjusted using rain gauges, which allows to minimize its correlation with errors found in flow predictions. When analyzing different types of rainfall input, one of the conclusions drawn by Löwe et al. (2014) was that radar rainfall observations and forecasts can improve probabilistic runoff predictions in the models, compared with those based on rain gauges. Additionally, the author mentions that adjusting radar data to closely resemble observations of rain gauges will consequently improve these model results. In terms of different lead times for nowcastings, Achleitner et al. (2009) reported that weather radar data with forecast horizons larger than 90 minutes leads to large deviations in the forecast for precipitation and sewer variables, such as CSO volume for small sub-catchments.

In response to rainfall input uncertainty, some researchers have used an additional model, named Numerical Weather Prediction (NWP) to generate ensemble forecasts that consist in a merging of radar nowcasts with NWP forecasts, to test their applicability for flow prediction (Liguori et al., 2012; Schellart et al., 2014). In these studies, the ensemble forecasts provided better flow prediction results and were improved, by the integration of NWP, for longer lead times (i.e., above 90 min), compared to radar rainfall forecasts. Courdent et al. (2015) evaluated the improvements in the performance of an UDS when applying a model predictive control with long ensemble forecast (i.e., up to 48 hours), from an NWP model. The CSO volume was estimated for the entire horizon and the different sensitivities of the receiving water bodies were determined as a cost per volume of CSO. For the rain events tested, the implementation of long forecast improved the mitigation of CSO volume in vulnerable areas, leading it to low sensitive locations. The authors concluded that these ensemble scenarios can handle the uncertainty of the forecasts. However, further investigation is required to develop appropriate measures to accurately compare radar rainfall forecasts with ensemble forecasts.

Verworn and Krämer (2005) investigated the combined use of three models (i.e., for radar rainfall forecast, rainfall-runoff simulation and decision finding) to operate and control urban drainage systems. To clarify, this combined approach has two simultaneous simulations, online and forecast, which allows to keep track of the current state and simulate the future situation for the system. The latter is then used by the decision finding model to generate an optimized course of action, based on the “cost” factors for the system. Following the comparison of static, local and global control for a case study, involving two detention ponds and a river with limited flow capacity, it was concluded that global control demonstrated a better performance. Nevertheless, both local and global control combined with the use of rainfall and runoff forecast are preferable to the static control. Although, there were expected differences in rainfall, the control strategies applied did not differ between runs with “realistic” radar rainfall forecast and perfect forecast. Moreover, when applying control strategies, according to the researchers, it is important to evaluate the differences between the two forecasts and analyze the results of both predictions, in terms of performance. However, both rainfall forecasts were generated by the researchers, and it would be interesting to determine the performance of real radar forecast compared with the perfect forecast.

Pleau et al. (2005) presented the global optimal control (GOC) implemented on the Quebec Urban Community’s (QUC) Westerly sewer network, to reduce frequency and volume of CSO discharged into two rivers (St. Charles and St. Lawrence), and its performance during three years of operation. This control software was used to compute, every 5 min, the optimal flow set points that were applied at the five control stations during normal wet weather conditions. The inputs collected to generate these set points included present and future rainfall intensities obtained from a meteorological forecasting model (i.e., CALAMAR), rain gauge measurements, flow rates and volumes measured at the local stations. During dry weather conditions, all the control locations operate in “static” mode, where the gates are positioned to prevent water retention in storage facilities and to treat peak dry weather flows at WWTP. The results were simulated using a hydrological and hydraulic model, named SWIFT, that computed flows and water levels in the sewer network for over a two-hour control horizon. Compared with static management strategies, the GOC implemented allowed a decrease of CSO volumes at four overflow sites by more than 87% for seven rainfall events in 1999. In the other two years (2000 and 2001), for a total of 98 storm events, GOC achieved a CSO volume reduction varying from 75% to 85%. However, this strategy only controls the flows conveyed to the WWTP based on information about its primary and secondary capacities, it does not include the evaluation of the performance of the treatment and quality of the effluent.

The applicability of real radar rainfall forecasts over a two-hour horizon as an input to model simulations was investigated by Löwe et al. (2016), for a case study in Copenhagen. One of the objectives of this research was to assess the improvements in control efficiency when considering forecast information and uncertainty, compared with optimization based on current basin fillings only. For this, seven control points were selected, and these are, usually, located at major actuators (e.g., the outlet of storage basins or pumping stations). The optimization of the outflow set points for the actuators was performed by the dynamic overflow risk assessment (DORA) algorithm, accounting for both forecasting uncertainty and impact cost, prioritizing more sensitive locations. Different five scenarios were compared for the seven control points, in terms of overflow volume reduction and cost accumulated over a number of rain events. The scenarios included two with the use of “perfect” gauge-based rainfall observations (i.e., ex-post hindcasting, the application of forecasting to past data), with and without uncertainty, two with real radar-based forecast, with and without uncertainty, and a reference (with no forecast). The results showed that a higher runoff forecasting skill was obtained for the perfect rainfall forecast derived from rain gauge measurements, compared with radar rainfall forecasts. Additionally, the estimated uncertainty of the model states was larger for real radar forecast, due to larger forecasting errors. However, the real forecast still greatly reduced the amount of overflow volume compared to the reference scenario. It is also reported that radar rainfall input can increase the reliability of the model during dry weather flow periods and that data with short lead times is preferable. Following the studies described above, as Lund et al. (2018) mentioned, the only paper that clearly states that actual rainfall forecast data has been used for the implementation of RTC in an urban drainage system is Löwe et al. (2016).

2.5. Summary

There is an extensive amount of literature related with RTC implementation, where the tendency seems to suggest that volume-based control is more commonly applied. The performance indicators mainly selected are CSO volume and frequency and investment cost savings, which allow to verify that the control strategies developed have the potential to mitigate impacts on the receiving watercourses and reduce the investments in CSO controlling and new infrastructures. The different RTC strategies used in the studies have both advantages and disadvantages, thus the comparison between these is frequently made. There is a continuous debate about which strategy is better and, although, some studies state that the optimal control, such as MPC, outperforms heuristic control, the RTC performance is strongly dependent of the urban drainage system selected for its implementation. The same logic can be applied for global and local control, the preference for one of these cannot be easily generalized.

However, the research work presented exposes the potential of RB-RTC for volume-based control, which achieved a reasonable CSO volume reduction compared with MPC. This raises the question of if the performance of RB-RTC could be enhanced. Despite the uncertainties associated with the data, the implementation of rainfall forecast has also proven to generate good results. Although, "perfect" rainfall forecast has been considered better than radar rainfall forecast, the latter also improves the performance of the control strategy. Therefore, the implementation of RB-RTC and radar rainfall forecast in an urban drainage system is an interesting combination to investigate and assess the possible benefits and risks.

To simplify the methodology of this approach and to adapt it to a more "realistic" scenario, it is preferable to use real radar rainfall forecast, provided by a meteorological institute, but uncertainties related to this data are still expected. For this reason, two factors can be considered when utilizing the forecast, which is a short lead time and processing the data in a binary method. According to the studies, lead times above approximately 2h increase the uncertainty of the forecast, but the system actuators also need the time to perform the control actions. A short lead time of 2h for the forecasts should allow sufficient actuator time reaction without increasing significantly the uncertainties. Regarding the binary method, it consists in processing the rainfall data and converting into 0 and 1 values, where 0 means that there is no rain forecasted and 1 is the opposite. Instead of developing a control strategy that is activated based on the exceedance of rain intensity or total depth thresholds, which requires a more accurate forecast to not overestimate or underestimate the storm event, using this binary data may reduce these issues. Research work and studies concerning the implementation of rainfall forecasts with the application of this method were not found, thus the benefits and risks of this approach should be determined. Besides, even considering these two factors, the accuracy of the real radar rainfall forecast compared with the observed rain data should be analyzed. Finally, to the best of the author's knowledge, the assessment of volume-based heuristic predictive control, using real radar rainfall forecast, has never been performed.

3. Methodology

3.1. General

Following the literature review, the main question of this dissertation focuses on the possibility of enhancing volume-based RB-RTC with radar rainfall forecast data. To perform this study, a full-integrated catchment model was selected, as it reduces the complexity of the system and allows to evaluate simultaneously the dynamics of the sewer system and WWTP. The model generated outputs were also assessed to determine its accuracy compared with monitoring data and its reliability to be used for simulation purposes.

Since rainfall data is a source of uncertainty in modelling, in this study, binary radar rainfall forecast is generated with the purpose of attempting to mitigate this factor. The binary real rainfall data is later compared with the observed rainfall data, to evaluate its accuracy. Additionally, RB-RTC can potentially benefit from this binary rainfall, because it allows the set of "if-then" rules to only focus on the expectance of rain and not on a particular interval of rain intensity or total depth values.

In this chapter, a methodology is proposed with the purpose of applying volume-based RB-RTC with binary radar rainfall forecast data on the case study of Eindhoven's IUDS. For this research, two control strategies were developed and analyzed. The objective of these strategies is to investigate how binary radar rainfall forecast data can be a benefit or a risk in the process of minimizing or preventing CSO incidents, without affecting the performance of the WWTP and increasing the NH_4 peaks in the receiving waters.

The subchapter 3.2 describes the type of model used to implement the control strategies in the system, introduces the required data to proceed with this research and proposes a model calibration procedure. In subchapter 3.3, the objectives, actuators, design and evaluation process of the control strategies developed are explained. Finally, the case study is presented in subchapter 3.4, describing the Eindhoven's IUDS, model software, monitoring data, model calibration, control implementation and evaluation process.

3.2. Calibration Procedure

A full-integrated catchment model was selected for this study, as it describes the hydrology, hydraulics, water quality and pollution transport in an urban drainage system and accounts for parameters (e.g., infiltration, depression storage, pervious/impervious area fraction). This information is relevant because CSO volume reduction can depend on the WWTP functioning at full capacity, and, consequently, affect the treatment plant's performance. Therefore, both of these sides need to be evaluated, to increase the reliability of the RTC strategies in the enhancement of the urban drainage system's performance.

When carrying out an assessment of volume-based heuristic predictive control, observed radar rainfall data, measured in the relevant locations of the integrated urban drainage system selected for the study, is needed for the available time period. This will serve as input to the full-integrated catchment model to generate the hydraulics and overall dynamics of the system.

To calibrate and validate the model, monitoring data obtained for locations within the sewer system is required. This data can consist in outflow measurements collected in particular sections, allowing its comparison to model generated data and to determine the accuracy of an IUDS model results.

Predictive control is implemented using actual radar rainfall forecast data, for the same time interval as the observed data. The forecast lead time should not exceed 2h, as the uncertainty of the rain data has shown to increase with longer lead times (e.g., Achleitner et al., 2009).

The full-integrated catchment model must be calibrated and validated for both dry weather flow (DWF) and wet weather flow (WWF). For this, a simulation is run for the entire time interval and storm events, that lead to a significant increase in the water level and/or CSO incidents in the system, are identified. These events must have a diversity of characteristics, such as different total rain depths, maximum intensities and duration, and be deemed sufficient for evaluating the model's flow dynamic. A group of relevant locations/actuators in the urban drainage system, that are essential for control implementation or lead to significant impacts in the receiving water bodies, also need to be defined.

Depending on the monitoring data available, the model results generated for the selected locations are compared with actual observed data concerning a particular variable (e.g., outflow at the pumping station). This comparison is analyzed through Nash-Sutcliffe Efficiency (NSE, Nash and Sutcliffe, 1970) coefficient values. The NSE coefficient allows to verify the fit between the model derived flow and the monitoring values, through the following mathematical expression:

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Obs_i - Sim_i)^2}{\sum_{i=1}^{n}(Obs_i - \overline{Obs})^2} \tag{3.1}$$

where Obs_i corresponds to the monitoring or observed data values, Sim_i is the model simulated results and $\overline{Obs}$ is the mean value of the monitoring data. This coefficient is dimensionless and it ranges from 0 to 1. For instance, NSE=0 is an indication that the model simulated results have the same accuracy as the mean value of the monitoring data, thus the use of the model can become impractical. Conversely, NSE=1 represents a perfect match between the model simulated and the monitoring values. Additionally, if the NSE<0, then the mean value of the monitoring data becomes a better predictor than the model simulations. Based on a review of published literature, Moriasi et al. (2007) established the general performance ratings for NSE for a monthly time step to determine how decent is the resemblance between simulated and observed data (Table 3.1).

Table 3.1 – General performance ratings for NSE for a monthly time step (adapted from Moriasi et al., 2007).

Performance Rating	NSE
Very good	0.75 < NSE ≤ 1.00
Good	0.65 < NSE ≤ 0.75
Satisfactory	0.50 < NSE ≤ 0.65
Unsatisfactory	NSE ≤ 0.50

According with the results obtained, a manual calibration, mainly based on a trial-and-error approach, can be performed to adjust and minimize the differences between model simulation results and the measurements collected. For this, model parameters that influence these differences need to be selected and adjusted based on the NSE coefficient values analysis for each simulation. The timing of the storm events also needs to be assessed.

3.3. Control Implementation

The main objectives of the control strategies need to be defined and based on the major issues in the urban drainage system selected for the study (e.g., CSO volume, NH_4 peak load). The definition of an objective function is essential to assess the performance of these strategies and to improve the development of the control procedures that aim at determining the optimum control actions and minimizing this function (e.g., Rauch and Harromoës, 1998; Duchesne et al., 2004).

While defining the objective, the main actuators and control locations need to be established, as well, to structure and develop these control procedures in the model. These components can be selected based on their influence on the system, in terms of flow representation, and proximity to sensitive areas. The control is then implemented in the model using on/off controllers, which set one of two control action values based on an interval of measurements of a specific parameter or variable. If the measured value is within the interval, then the "on" value is chosen. On the other hand, if the measured value is not within the interval, then the "off" value is used. The controllers account for input variables and parameters (e.g., filling degree of the upstream section of the system) to generate the control actions. The set values for each controller can be defined through several iterations run in the model that allow the minimization of the objective function.

To evaluate the performance of the control procedures developed, perfect and real radar rainfall forecast are used. The results obtained for both forecasts are compared based on performance indicators (e.g., CSO volume reduction) for a selected number of storm events with different characteristics. The reference scenario is the standard functioning of the system (i.e., control off). The perfect rainfall forecast was derived from the observed radar rainfall data for the same forecast horizon as the real radar rainfall forecast. Both this data and the real rainfall forecast data, described in subchapter 3.2, can be processed in a binary approach, where the value 0 means that no storm event is expected over a particular horizon, and the value 1 represents the opposite.

This expectance of a storm event can be established based on thresholds of one or multiple rainfall parameters, such as total rainfall depth, maximum rainfall intensity and duration. For instance, considering only total rainfall depth, if a storm event is defined by a maximum value of the total rainfall depth forecasted over a two-hour horizon that exceeds 0.50 mm, it leads to a binary representation of the continuous matrix (Figure 3.1). This is a simplified layout developed to illustrate the data generating process for this particular example.

The radar rainfall forecast data (Figure 3.1a) is received and processed, where the maximum of the total rainfall depth values (in mm) of each pixel is converted into ones, if this maximum exceeds the threshold 0.50 mm, and into zeros, otherwise. This process generates the binary radar data (Figure 3.1b), where the pixel region with the values 1 corresponds to the area that is expecting a storm event over the established horizon. This binary method can also account for different total rainfall depth thresholds, to assess what these imply for the performance of sewer system, compare their results and determine which one is preferable.

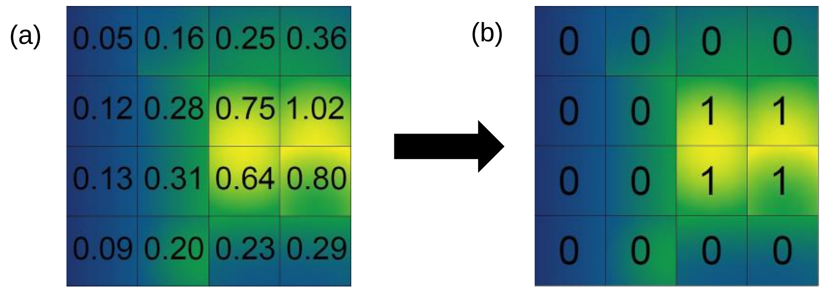

Figure 3.1 – Simplified layout of the binary radar data generated in this process.

The binary real forecast was compared to the perfect forecast using a contingency table, showing the frequency of “yes” and “no” forecasts and occurrences (Reyniers, 2008). Since this perfect forecast was derived from the observed rainfall data, it can be used to assess the accuracy of the real forecast data. Table 3.2 presents the structure used for this contingency table.

Table 3.2 - Contingency table regarding binary real forecast and observed data.

		Observed	
		Yes	No
Forecast	Yes	Hits	False Alarms
	No	Misses	Correct Negatives

When a storm event in the observed data is forecasted, it counts as a “hit”, otherwise, it is named “miss”. If no storm events are observed and forecasted, then it counts as “correct negatives”, but, if a false storm event is forecasted, then it results in a “false alarm”.

This information can be used to calculate the following verification statistics (Gagne et al., 2014):

$$Probability\ of\ detection\ (POD) = \frac{Hits}{Hits + Misses} \tag{3.2}$$

$$False\ alarm\ ratio\ (FAR) = \frac{False\ Alarms}{Hits + False\ Alarms} \tag{3.3}$$

$$Probability\ of\ false\ detection\ (POFD) = \frac{False\ Alarms}{False\ Alarms + Correct\ Negatives} \tag{3.4}$$

The probability of detection (POD) represents the ratio of hits to the total number of observed storm events. The false alarm ratio (FAR) is the number of false alarms compared to the total of "yes" forecasts. Finally, the probability of false detection (POFD) consists in the ratio of false alarms to the total of "no" observed storm events. While the value of POD gets better as it approaches one (100%), the FAR and POFD values will be better if it gets closer to zero (0%) (Sofiati and Nurlatifah, 2019). These verification statistics derived from the contingency table have the purpose of evaluating the accuracy of the real radar rainfall forecast data compared with the observed data.

The difference between the control strategies implemented can be determined through a statistical significance analysis, including hypothesis tests, such as, Kolmogorov–Smirnov (K-S) test. For instance, the two sample K-S test verifies if the null hypothesis, that the data in vectors x1 and x2 belong to the same continuous distribution, is rejected at a particular significance level (e.g., 5%), meaning that the vectors are from different continuous distributions, or not rejected (Massey, 1951).

3.4. Case Study

3.4.1. Eindhoven IUDS

The urban drainage system of Eindhoven was selected as the case study to assess the implementation of volume-based heuristic predictive control. There are three main components related to this IUDS, which are: three contributing sewer catchments, WWTP and the river Dommel (Figure 3.3).

The three main sewer catchments are Eindhoven Stad, Nuenen-Son and Riool Zuid. Eindhoven Stad only serves the city of Eindhoven and represents about 45% of the WWTP influent. While Riool Zuid also constitutes 45% of the total WWTP influent, it serves seven municipalities through a 31 km transport sewer. Nuenen-Son only serves two municipalities and represents less than 10% of the total inflow (van Daal-Rombouts, 2017). In addition, the entire IUDS has about 29 urban drainage networks and more than 200 CSOs along the river Dommel and its tributaries.

Regarding the WWTP of Eindhoven, it is one of the largest plants in the Netherlands, designed for a 750 000-population equivalent and with three biological lines with a combined capacity of 26 250 m^3/h. Each biological line is composed of one primary clarifier (PC), a biological treatment tank and four secondary clarifiers (SC). Besides, there is a by-pass leading to a storm settling tank (SST) with an extra capacity of 8750 m^3/h, which is emptied into the WWTP after a storm event, becoming an additional inflow (Moreno-Rodenas, 2019). In standard control, the total influent is split equally over the three treatment lines and one water line. The operation of the three primary clarifiers is similar and continuous. During DWF conditions, these clarifiers are filled with raw sewage and have a hydraulic retention time of four hours, which is reduced for one hour when influent flows reach the maximum value. At the start of storm events, the stored concentrated sewage is transported to the activated sludge tanks, at a WWF rate. This can result in peak load to the aeration tanks and, consequently, increase NH_4 concentration in the WWTP effluent. The SST operates during all storm events.

In Figure 3.2, a schematic overview of the WWTP of Eindhoven can be observed, along with the locations of the measurement devices.

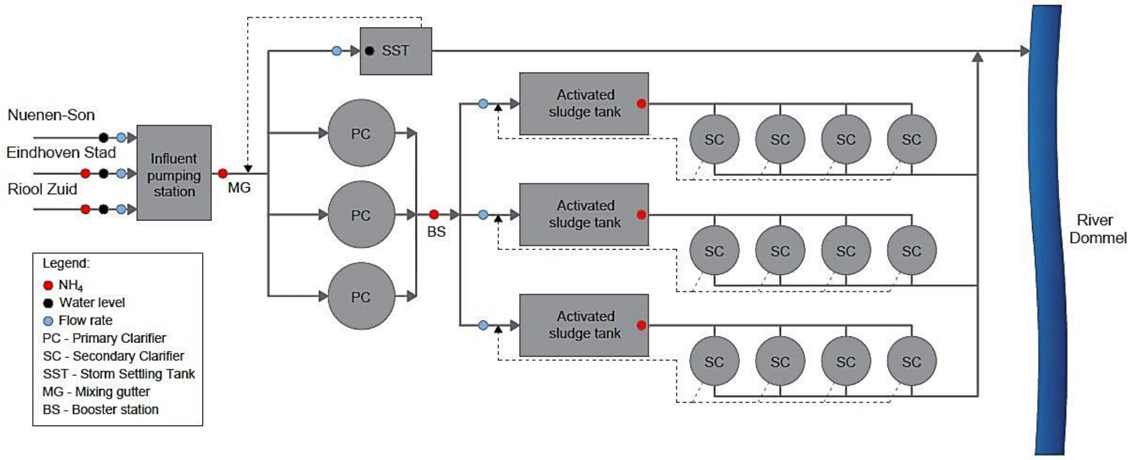

Figure 3.2 - Schematic overview of the WWTP of Eindhoven (adapted from van Daal-Rombouts, 2017; Moreno-Rodenas, 2019)

The treatment plant performs measurements of the influent flows and water levels from the three influent chambers, flow and water level in the storm settling tank and the flows to the activated sludge tanks. Additionally, NH_4 concentration measurements are obtained in the influent flows of Eindhoven Stad and Riool Zuid, in the mixing gutter before the primary clarifiers, in the flow towards the booster station and in each activated sludge tank. Moreover, all flow and water level measurements are near continuously available in the WWTP supervisory control and data acquisition (SCADA) control system, and NH_4 measurements are performed every five minutes. Besides, water levels (i.e., Vega, Vegabar 66) at all CSOs in the contributing sewer catchments are measured at a one-minute time step (van Daal-Rombouts, 2017).

Finally, the Dommel river is identified as a small lowland river, which originates in Belgium and flows north until it reaches the river Meuse. Its base flow can vary from 1 to 30 m^3/s, but during dry summer periods, the flow can lower to 1 m^3/s. The major issue with this river is that, during the dry weather, it consists of as much treated effluent as its original water, but, during wet weather, around 90% of the river water consists of WWTP effluent. (van Daal-Rombouts, 2017; Moreno-Rodenas, 2019*)*. Consequently, this can lead to the water quality concerns mentioned before, such dissolved oxygen depletion due to CSO discharges and WWTP effluent and toxic NH_4 peaks due to the WWTP effluent, since NH_4 concentration levels of CSO spills are usually significantly lower (Langeveld et al., 2013).

An overview of the urban drainage system of Eindhoven is presented in Figure 3.3.

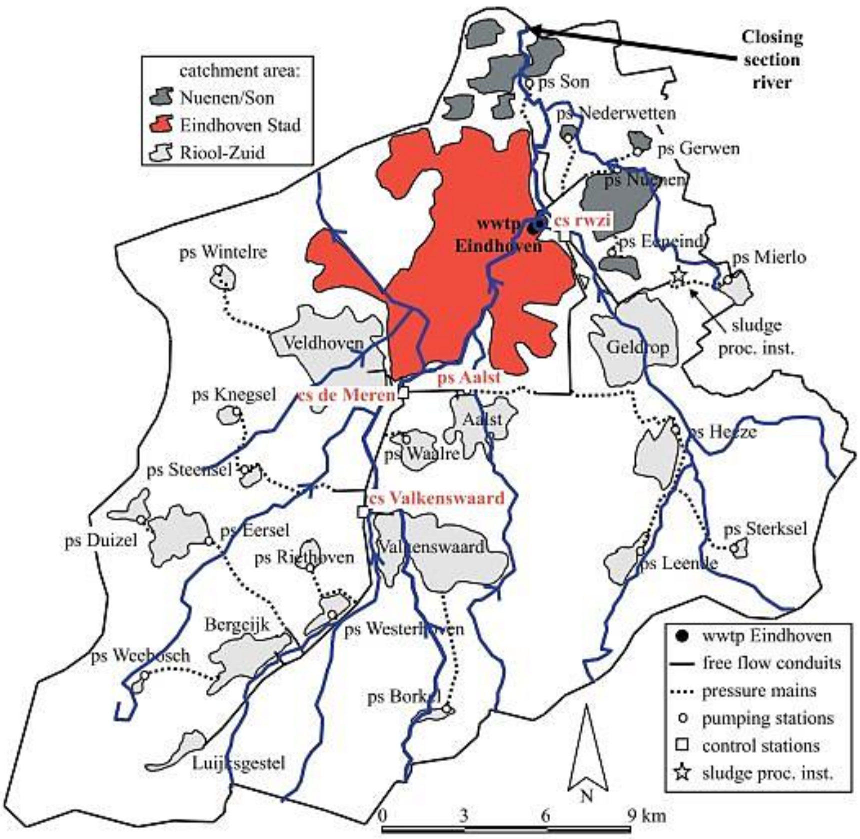

Figure 3.3 - Overview of urban drainage system of Eindhoven (adapted from Langeveld et al., 2013).

Besides the characteristics described above, there are four main reasons that make Eindhoven's water system a suitable case study (van Daal-Rombouts, 2017; Moreno-Rodenas, 2019):

- The catchment covers an area of more than 800 km^2;
- WWTP influent from three separate sewer catchments;
- Transport sewer Riool Zuid is equipped with one pumping station and three control stations (which are presented in Figure 3.3, orange colored and initially named "ps" and "cs" respectively);
- A diversion works in the river Dommel just south of Eindhoven.

Given the reasons mentioned above, the significant covered area is important because it allows for a heterogeneous distribution of the rainfall, which is relevant to determine how it can affect the heuristic predictive control developed. As a result, according to the second reason, the maximum WWTP inflow for those storm events is prone to arrive at different times for the three sewer catchments. Besides, the pumping and control stations and the river diversion allows a potential control implementation in this IUDS, to interfere with its operation (e.g., delay or level out high inflows from Riool Zuid) and/or its impact on the river.

This is consistent with the outcome of the PASST (Planning Aid for Sewer System Real Time Control) planning tool (Schütze et al., 2008), which is a methodology used to screen an IUDS for its control potential that revealed that the Eindhoven system was "suited for control" (Langeveld et al., 2013). In addition, the Waterboard of the Dommel (the public company responsible for the quality of the Dommel River, the Netherlands) envisioned a series of substantial investments (Benedetti et al., 2013) aiming to improve the ecological status of the river Dommel. Therefore, a full-integrated catchment model was developed (Langeveld et al., 2013) as an output of the Kallisto project (Weijers et al., 2012), aiming towards a better understanding of pollution dynamics in the system and simulating the link between the WWTP, all relevant urban and rural contributing areas and the receiving water body (the Dommel and its tributaries), thus modelling the dynamics of DO and NH_4 impacts in the river (Moreno-Rodenas, 2019).

3.4.2. Description of the model

As it was stated in the previous subchapter, a full-integrated catchment model was built for Eindhoven IUDS, with the purpose of exploring the use of RTC in this suitable system. The model is associated with a software package, named MIKE (DHI Software, www.mikepoweredbydhi.com), particularly WEST software, that allows to implement advanced control strategies and run simulations of complex/ integrated models in one platform.

In this model platform, the urban catchments are represented by a hydrological structure for the rainfall-runoff response, that accounts for wetting losses, and a tank-in-series routing scheme that simulates gravity and pressurized sewer transport. As for the WWTP, it was simulated with an ASM2d biokinetic model and the link between in-sewer water quality and the WWTP influent was represented by an empirical influent model (Gernaey and Jørgensen, 2004; Langeveld et al., 2017). Finally, the Dommel river was also modelled through the use of tank-in-series, with the purpose of representing an approximation of the flow propagation process, and the physical and biochemical reactions were also accounted for (Moreno-Rodenas, 2019).

Given the above, this full-integrated catchment model was selected over a full hydrodynamic model, because it provides crucial information about the dynamics of the WWTP and the NH_4 effluent concentrations.

3.4.3. Monitoring Data

For the case study selected, observed radar rainfall data is available from the Royal Netherlands Meteorological Institute (KNMI). This data is defined by a five-minute interval and pixel size of 1x1 km from January 2014 to December 2015 and January 2019 to December 2019 and it is adjusted against rain gauge measurements, as explained previously in Chapter 1. The rainfall data was collected for the relevant municipalities located in Eindhoven and connected to the three primary sewer catchments (i.e., Riool Zuid, Eindhoven Stad and Nuenen-Son), as presented in Figure 3.3.

Regarding the radar rainfall forecast data, it was also provided by KNMI, with the same characteristics presented above, but only the period of January 2014 to December 2015 was accessible. The forecast lead time is 2h and the collection procedure for this particular data will be further explained in subchapter 3.4.5.3.

Moreover, monitoring data at the sewer system control station De Meren and pumping station Aalst, from May 2019 to December 2019, was collected for the model calibration procedure described in the subchapter 3.4.4. This data is available at a one-minute interval, and it represents the outflow measurements obtained at the two locations mentioned previously.

3.4.4. Calibration

Before running the relevant simulations for this study, a model calibration was performed. First, the observed radar rainfall data, from 2019, was processed and imported to the WEST model, using MATLAB software, so the flows and water levels could be generated for the respective locations. The radar rainfall input to the model is performed individually for each catchment and sub-catchment. Accordingly, the model was used to run a simulation through the entire year of 2019, analyzing both DWF and WWF, and with the purpose of identifying events that led to a significant increase in the water level and/or CSO incidents in the system.

These issues were verified for a selected group of important locations in the system that are either essential to implement control strategies or lead to the significant impacts, mentioned in previous chapters, in the river Dommel. The selected locations are control stations (CS) Valkenswaard and De Meren, pumping station (PS) Aalst, the three primary catchments (i.e., Riool Zuid, Eindhoven Stad and Nuenen-Son) influent chambers to the WWTP and CSO Bergeijk, Loondersweg, Krooshek and Eindhoven. These sections of the system are represented in the model as tanks, to simulate the dynamics of sewer pipes. Through the described simulation, 15 storm events were selected and deemed sufficient for evaluating the model's flow dynamic. These events and their characteristics are summarized in Table 3.3.

Table 3.3 - Selected storm events from 2019 with key characteristics.

Event (dd - mm)	Total Rainfall Depth (mm)	Maximum Rainfall Intensity (mm/h)	Duration (h)
19 May to 20 May	7.92	44.94	7.93
28 May	0.20	1.18	0.84
4 June to 5 June	21.52	138.07	7.69
12 June	5.41	38.26	6.66
12 July	3.37	29.16	3.45
27 July	1.60	7.39	5.26
9 August	7.17	15.26	6.82
29 August	10.53	53.94	2.67
1 October	21.12	46.12	12.40
4 October	23.69	33.98	15.86
16 October	5.00	18.31	3.83
3 November	3.66	7.54	8.23
27 November	19.13	9.62	16.17
13 December	23.46	13.66	21.56
22 December	4.21	16.22	5.65

This heterogeneity of events is required to perform a model calibration that accounts for different scenarios in the sewer system. For each event, the outflow values obtained for the CS De Meren and PS Aalst were collected to compare with the monitoring data for the same locations, mentioned in the previous subchapter. The monitoring data for both locations was smoothed by determining an hourly mean of the outflow measurements to avoid intermittent fluctuations in the data that could influence the comparison results.

The comparison between the model generated and monitoring data was analyzed through NSE (Nash and Sutcliffe, 1970) coefficient values. The final NSE results are presented and discussed in Chapter 4. The timing of the storm events selected for this calibration was also compared between the model generated and monitoring data. In this study, to better understand the functioning of the full-integrated model, the author performed a manual calibration, based on a trial-and-error approach. While the NSE values were evaluated, the model parameters were adjusted to minimize the differences between the model simulation results and the measurements obtained. The parameters selected for the calibration procedure, their respective units and the search range are presented in the Table 3.4.

Table 3.4 - Identification of calibration parameters and search range.

Model parameter	Abbreviation	Unit	Search Range
Fraction of volume	f_on	-	0.05 – 0.4
Maximum depression storage	MaxDepressionStorageImp	mm	2 - 5

It is important to notice that the search range is based on the testing boundaries established for the parameters, and the selected values for each will be presented in Chapter 4. Observing Table 3.4, the parameter f_on corresponds to the fraction of volume above which the outflow is equal to the pumping flow (Qout=Qpump) and it is dimensionless. As for the second parameter, it is related to the maximum depression storage (in mm) for impervious areas in the different municipalities. Since the monitoring data was only available for CS De Meren and PS Aalst, the parameters presented previously were calibrated upstream of Aalst. Therefore, only an upstream validation was performed, as the remnant part of the Eindhoven system was assumed to be sufficiently calibrated, by the previous model users (i.e., Moreno-Rodenas et al., 2019), for the model simulations required.

3.4.5. Control Implementation

Following the calibration procedure, two control strategies (i.e., control strategy 1 and 2) were implemented in the model to assess volume-based RB-RTC with binary radar rainfall forecast data. The next equation translates the objective function developed to assess and improve the control procedures.

$$\min_{S_n(t)} \sum_{i=1}^{N} V\big(S_n(t)\big) + W\big(S_n(t)\big) \tag{3.5}$$

Where N is the number of storm events used for the determination, V is the total CSO volume at each time interval t, W is the duration of the peak load in the WWTP at each time interval t and S_n is the setting for the n-actuators in the system subject to:

$$S_n = \begin{cases} if\ r_n = 1 \begin{cases} s_1\ if\ f_n > threshold \\ s_2\ if\ f_n \leq threshold \end{cases} \\ if\ r_n = 0 \begin{cases} s_3\ if\ f_n > threshold \\ s_4\ if\ f_n \leq threshold \end{cases} \end{cases} \tag{3.6}$$

Where s_1, s_2, s_3 and s_4 are the optimal set values for the control actions, r_n is the binary radar rainfall forecast and f_n is the filling degree at a particular section of the system relevant for the activation of n^{th}-actuator and the threshold corresponds to the limit value that triggers the control actions. If r_n = 0, then no rainfall is expected in 2h. If r_n = 1, then rainfall is expected in 2h.

Both strategies aim at minimizing total CSO volume without significant additional overflow volume in the system and overcharging the WWTP and their control procedures will be further explained in the next subchapters.

3.4.5.1. Control Strategy 1: development of control procedures

The control strategy 1 focuses in providing space in the sewer system and using the WWTP at maximum capacity, to manage the rainfall forecasted over a two-hour horizon and minimize total CSO volume. At the same time, it should avoid significant additional overflow volume and the increase of the peak load in the WWTP.

Since the Eindhoven system is “suitable” for control implementation, mainly due to the presence of actuators and the possibility of controlling the flow rate in certain locations, six control points were selected for this strategy. These control points are control stations Valkenswaard and De Meren, pumping station Aalst, Eindhoven Stad and Riool Zuid influent chambers to the WWTP and the storm settling tank at the WWTP.

This control was implemented in the model using on/off controllers, which set one of two control action values based on an interval of measurements of a specific parameter or variable, as described in subchapter 3.3. Moreover, in this procedure, the controllers use the data regarding the input variable “rain” and the parameter “filling degree” (FD) to generate the control actions. In this study, the filling degree of the selected sections of the system is prioritized compared with the expectance of rain, to avoid a potential increase in the number of CSO discharges and volume. The set values for each controller were determined through several simulation runs in the model that allowed the minimization of the objective function (equation 3.5) described previously. When no more improvements were achieved in the minimization of this function, it was assumed that an optimum procedure was found but this was not proven.

At the CS Valkenswaard, three on/off controllers were implemented. The controller 1 receives the rainfall forecast data upstream of this station and, depending on the information obtained, it either activates controller 2 or controller 3. Then, one of these last two controllers communicates to controller 1 the maximum effluent flow rate value allowed at the control station. According to the forecast data, if rain is expected in 2h, then controller 1 activates the controller 2. This second controller verifies the filling degree upstream of this location and based on that information, it determines the maximum effluent flow rate value allowed. Similarly, when rain is not expected in 2h, controller 3 is activated and also decides the preferable maximum effluent flow rate value to inform controller 1 based on the filling degree upstream. To illustrate, Figure 3.4 presents a schematic overview of the control actions and set values defined for CS Valkenswaard.

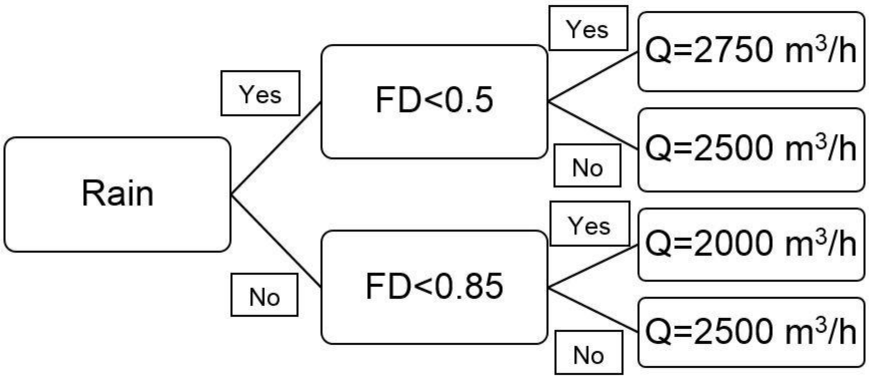

Figure 3.4 – Schematic overview of the control procedure applied at the control station Valkenswaard.

As it is displayed in Figure 3.4, one of the aims of this procedure is to increase the maximum effluent flow rate (Q=2750 m^3/h) when rain is expected and the filling degree is below a defined threshold (FD<0.5 or 50%), to provide space in the sewer system. If the filling degree is above the threshold, then the maximum flow rate is set at the standard value (Q=2500 m^3/h) for this location. However, the other aim is also to limit the maximum flow rate (Q=2000 m^3/h) when rain is not expected and the filling degree is below a selected threshold (FD<0.85 or 85%), to avoid overcharging the WWTP and the downstream catchments. If the threshold is exceeded, then the maximum flow rate is set at the standard value mentioned previously.

For CS De Meren, the same logic, described previously for Valkenswaard, was applied, implementing three on/off controllers that communicate about the rainfall forecast and filling degree upstream of this location and the maximum effluent flow rate allowed. Figure 3.5 shows a schematic overview of the control actions and set values established for CS De Meren.

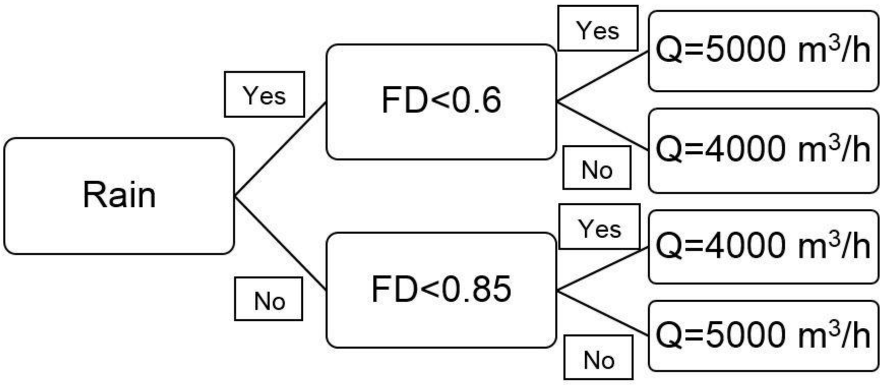

Figure 3.5 - Schematic overview of the control procedure applied at the control station De Meren.

The objective for this location is different, as the standard value (Q=5000 m^3/h) is set if the filling degree is below the threshold and a limit value (Q=4000 m^3/h) is selected if the filling degree exceeds that threshold. The set values were defined in this order to minimize the hydraulic loading to PS Aalst and reduce total CSO volume at CSO Krooshek. When a storm event is expected, the filling degree in this control station is above 0.6 (60%) and maximum effluent flow rate is set at 5000 m^3/h, CSO Krooshek (which is connected to PS Aalst) discharge volume is increased.

For this reason, by limiting effluent flow rate at 4000 m^3/h, the spare capacity upstream of De Meren is utilized and CSO Krooshek discharge volume is reduced. However, CSO Loondersweg discharge volume might increase slightly, as this CSO is located upstream of De Meren. When rain is not expected and the filling degree is below the threshold (FD<0.85 or 85%), the outflow is limited (Q=4000 m^3/h), but if the filling degree is above the threshold, the standard value is once again selected.

At the PS Aalst, only two on/off controllers are used. Controller 1 receives rainfall forecast data upstream of this site, and if a storm event is expected, the same controller sets the maximum pumping flow rate value. When rain is not expected, then controller 2 is activated and decides one of two set values for the maximum pumping flow rate. In Figure 3.6, a schematic overview of the control actions and set values defined for PS Aalst is presented.

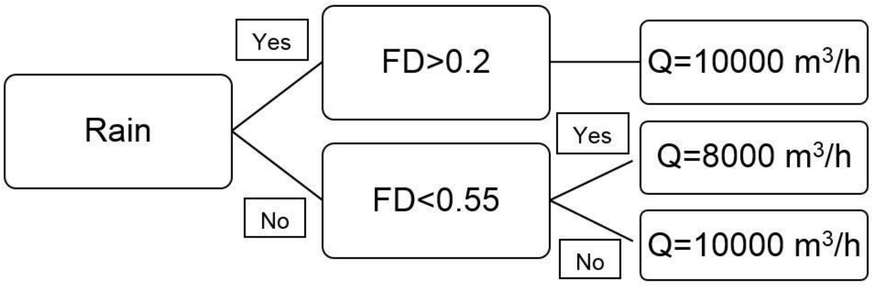

Figure 3.6 - Schematic overview of the control procedure applied at the pumping station Aalst.

If a storm event is expected in 2h, the pumping flow rate is set at the maximum value (Q=10 000 m^3/h). There is no limit value for this procedure, because it will only increase CSO Krooshek discharge volume, which is the CSO connected to this control location. In Figure 3.6, the filling degree must be above 0.2 (20%), otherwise it means there is not enough water in this location to be pumped. On the other hand, if rain is not expected and the filling degree is below the threshold (FD<0.55 or 55%), then a limit value (Q=8000 m^3/h) is set. If the filling degree is above the threshold, then the maximum value is once again selected to avoid a CSO or minimize its discharge volume.

For Riool Zuid's influent chamber to the WWTP, three on/off controllers were set with the same communication approach, as described for control stations Valkenswaard and De Meren. Figure 3.7 shows a schematic overview of the control actions and set values established for Riool Zuid's influent chamber.

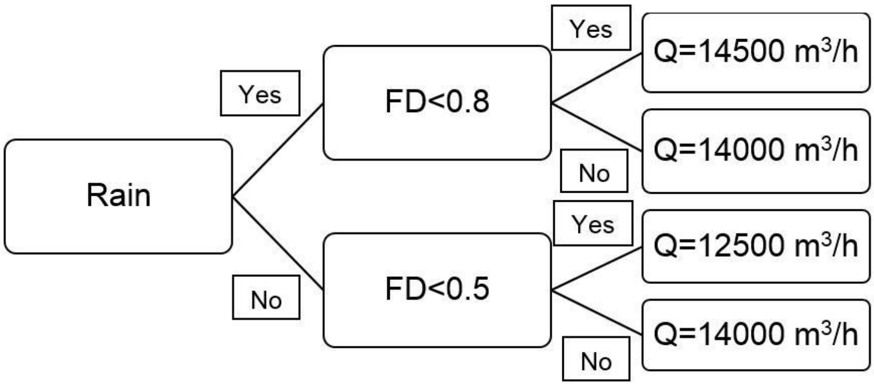

Figure 3.7 - Schematic overview of the control procedure applied at Riool Zuid's influent chamber.

If rain is expected in 2h and the filling degree is below the threshold (FD<0.8 or 80%), then the maximum effluent flow rate is set at 14 500 m^3/h. Otherwise, if the filling degree is above the threshold, the value defined for the maximum effluent flow rate is 14 000 m^3/h. On the other hand, when rain is not expected in 2h and the filling degree is below the threshold (FD<0.5 or 50%), the limit value (Q=12 500 m^3/h) is selected for the maximum effluent flow rate to not overcharge the WWTP. If the filling degree exceeds that threshold, then the maximum flow rate is 14 000 m^3/h.

Similarly, Eindhoven Stad's influent chamber has three on/off controllers, such as Riool Zuid, that present the same objectives and communication approach. The schematic overview of the control actions and set values defined for Eindhoven Stad's influent chamber is presented in Figure 3.8.

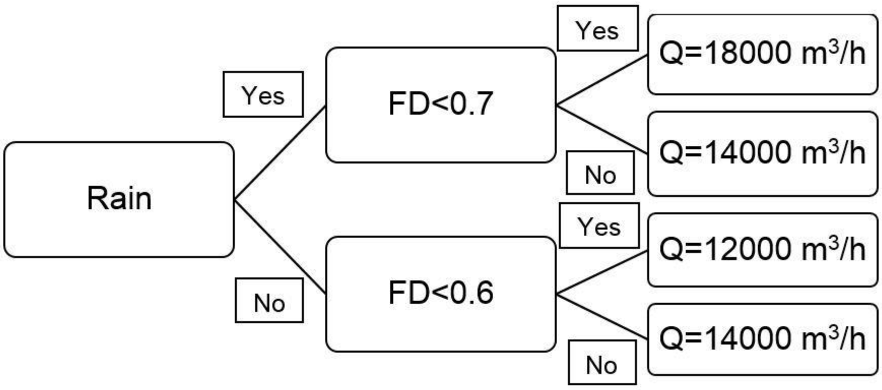

Figure 3.8 - Schematic overview of the control procedure applied at Eindhoven's influent chamber.

In this control point, when rainfall is expected and the filling degree is below 0.7 (70%), the maximum pumping flow rate is set at 18 000 m^3/h. This maximum value was chosen due to the high probability of CSO discharge and the necessity of providing sewer capacity for this location. When the filling degree is above the threshold, the maximum flow rate is set at a standard value (Q=14 000 m^3/h). If rainfall is not expected and the filling degree is below 0.6 (60%), then the limit value (Q=12 000 m^3/h) is selected for the maximum pumping flow rate. Otherwise, if the filling degree exceeds the threshold, then the standard value is chosen again. Regarding the SST of the WWTP, its operation is activated when a storm event is expected in 2h and deactivated otherwise.

3.4.5.2. Control Strategy 2: development of control procedures

The objective of control strategy 2 consists in utilizing the spare capacity of the system by limiting the flow upstream of the WWTP, when rainfall is expected over a two-hour horizon, to avoid an increase of peak load during these storm events. It should also contribute for a total CSO volume reduction and avoid significant additional overflow volume.

The six control points selected for this strategy are also control stations Valkenswaard and De Meren, pumping station Aalst, Eindhoven Stad and Riool Zuid influent chambers to the WWTP and the SST at the WWTP. This control used on/off controllers with the same approach, as described in the control procedures developed for control strategy 1, thus prioritizing the filling degree in the selected parts of the system compared with rain forecasted. Moreover, the group of set values for each controller were defined based on numerous iterations run in the model that allowed the minimization of the objective function (equation 3.5), as described in subchapter 3.4.5.1.

In CS Valkenswaard, there are three on/off controllers, where controller 1 activates controller 2 or controller 3 based on the information received about the rainfall forecast upstream of the site. When rainfall is expected in 2h, controller 2 is activated to communicate to controller 1 the control action determined, but if rainfall is not expected, then controller 3 decides the control action to inform controller 1. In Figure 3.9, a schematic overview of the control actions and set values defined for CS Valkenswaard is presented.

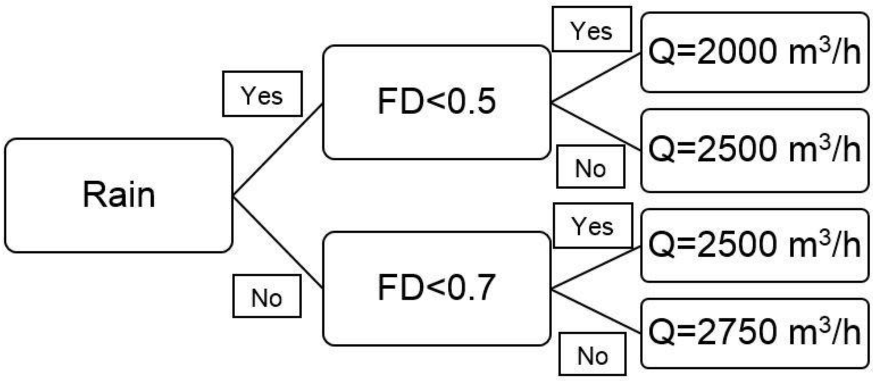

Figure 3.9 - Schematic overview of the control procedure applied at the control station Valkenswaard.

In this procedure, the objective is to start limiting the maximum effluent flow rate (Q=2000 m^3/h), when rainfall is expected in 2h and the filling degree is below 0.5 (50%), and then, if the filling degree exceeds the threshold, set it at the standard value (Q=2500 m^3/h) defined for this site. When rain is not expected, if filling degree is below 0.7 (70%), then the standard value remains, otherwise, if this section is reaching its full capacity, then the maximum effluent flow rate is set at 2750 m^3/h.

CS De Meren presents three on/off controllers, with the same approach as Valkenswaard, and the control actions and set values selected are displayed in Figure 3.10.

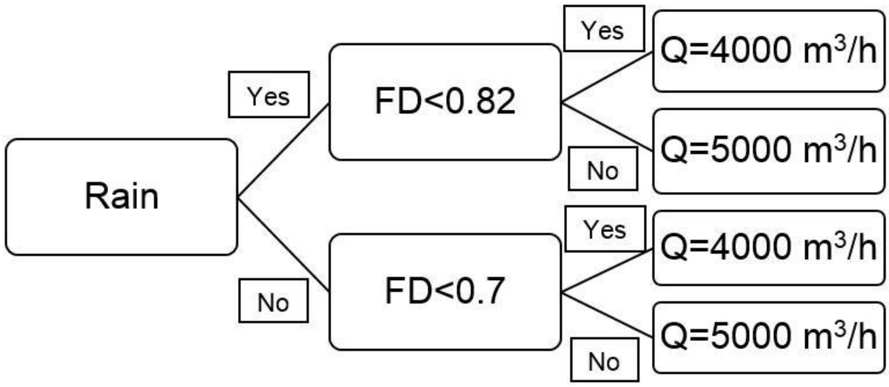

Figure 3.10 - Schematic overview of the control procedure applied at the control station De Meren.

If the rain is predicted and the filling degree is below 0.82 (82%), the maximum effluent flow rate is limited at 4000 m^3/h, otherwise, if the filling degree surpasses the threshold, then the standard value (Q=5000 m^3/h) is chosen. When rain is not forecasted in 2h, if the filling degree is below 0.7 (70%), then the limit value (Q=4000 m^3/h) is set. However, if the filling degree's threshold is exceeded, then the maximum is set at the standard value.

PS Aalst only presents two on/off controllers, where controller 1 receives the rain forecast input and either activates controller 2 or sets a determined value. The schematic overview of the control actions and set values established for PS Aalst can be observed in Figure 3.11.

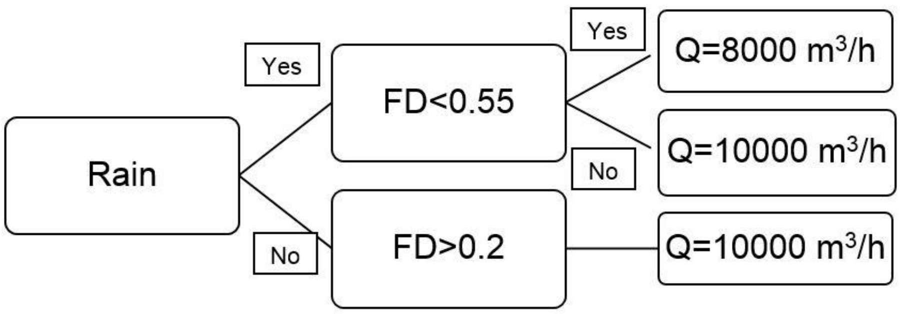

Figure 3.11 - Schematic overview of the control procedure applied at the pumping station Aalst.

The prediction of rain and a filling degree below 0.55 (55%) limits the maximum pumping flow rate at 8000 m^3/h, but if the filling degree surpasses the threshold, then the flow rate is set at 10 000 m^3/h. When rain is not expected, the maximum pumping flow rate value is 10 000 m^3/h.

For Riool Zuid's influent chamber, three on/off controllers have been established, with the same approach as control stations De Meren and Valkenswaard. The schematic overview of the control actions and set values defined for Riool Zuid's influent chamber is presented in Figure 3.12.

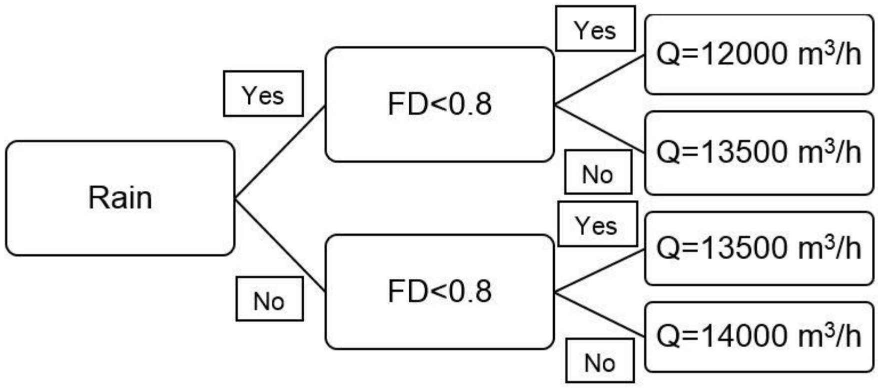

Figure 3.12 - Schematic overview of the control procedure applied at Riool Zuid's influent chamber.

The limit value (Q=12 000 m^3/h) is set when a storm event is predicted for the next 2h and the filling degree is below 0.8 (80%), but if the filling degree's threshold is exceeded, then the maximum flow rate is set at 13 500 m^3/h. When a storm event is not predicted and the filling degree is below the same threshold (80%), the maximum flow rate value remains 13 500 m^3/h, otherwise, if the filling degree's threshold is surpassed, then it is set at 14 000 m^3/h.

Similarly, Eindhoven Stad's influent chamber also has three on/off controllers, like Riool Zuid, and its control actions and set values are presented in Figure 3.13.

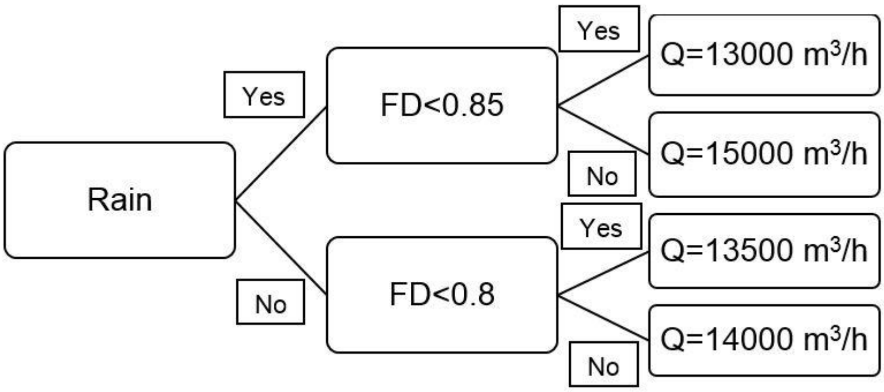

Figure 3.13 - Schematic overview of the control procedure applied at Eindhoven's influent chamber.

When rain is expected and the filling degree is below 0.85 (85%), the maximum pumping flow rate is set at 13 000 m^3/h, but if the filling degree exceeds the threshold, then the value is set at 15 000 m^3/h. If rain is not expected and the filling degree is below 0.8 (80%), then the maximum value is 13 500 m^3/h, otherwise, if the filling degree is above the threshold, then it is set at 14 000 m^3/h. The operation of the SST is also activated when a storm event is predicted in the next 2h and deactivated otherwise.

3.4.5.3. Evaluation

The performance of these control procedures, developed and described in the previous subchapters, was evaluated through model testing using perfect and real radar rainfall forecast. Perfect rainfall forecast is identical to the observed rainfall data, but it has a lead time of 2h. This forecast was generated for a two-year period, from January 2014 to December 2015. Since, this data is only necessary for the six control points defined, the total rainfall depth values upstream of each control location were determined. This data was processed in a binary approach for five different total rainfall depth thresholds, which are presented in Table 3.5. This perfect forecast was used to assess the accuracy of the real rainfall forecast, to validate the control procedures and to perform model simulations for each entire year.

Real rainfall forecast corresponds to the authentic prediction data generated and provided by KNMI, with a lead time of 2h. This forecast is available only for a two-year period, from January 2014 to December 2015. The data was collected for each municipality related to Eindhoven's IUDS, and it was also processed in a binary approach for five different total rainfall depth thresholds (Table 3.5). The total rainfall depth values were also determined upstream of each control point.

Table 3.5 - Total rainfall depth thresholds for the binary method applied.

Total rainfall depth thresholds (mm)	**If max total rainfall depth < threshold**	**If max total rainfall depth > threshold**
0.01	0	1
0.50	0	1
1.00	0	1
2.50	0	1
5.00	0	1

When the maximum value of the total rainfall depth forecasted over a two-hour horizon is below any of the five thresholds, the data assumes the value 0, meaning it is considered that no storm event is expected over that horizon. On the other hand, if this maximum is above any of the five thresholds, then the value 1 is selected, which means a storm event is forecasted over a two-hour horizon. The purpose of these thresholds is to evaluate how the control procedures perform when a storm event is only considered relevant above a particular total rainfall depth.

As described in subchapter 3.3, a comparison between the binary real forecast and perfect forecast is verified for the five total rainfall depth thresholds, using a contingency table, showing the frequency of "yes" and "no" forecasts and occurrences (Reyniers, 2008). Additionally, verification statistics were derived from the contingency table with the purpose of evaluating the accuracy of the real radar rainfall forecast data compared with the observed data.

To validate these control procedures using real forecast, 10 storm events were selected for each year (2014 and 2015). The performance of the control procedures and forecasts is compared and assessed, with the standard functioning of the system (i.e., control off), for the same events. The selected 20 events and their characteristics, such as total rainfall depth, maximum rainfall intensities and duration, are displayed, in chronological order, in Figures 3.14, 3.15 and 3.16, respectively.

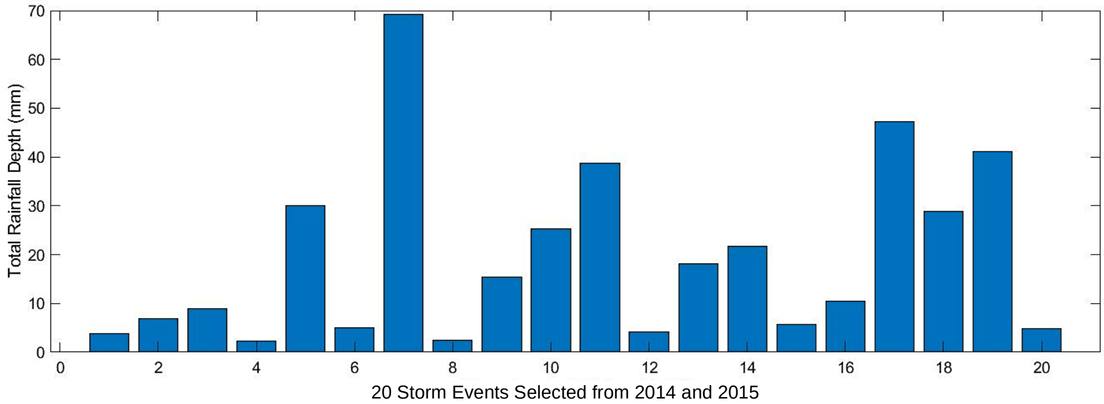

Figure 3.14 - Total rainfall depth for each storm event selected from 2014 and 2015.

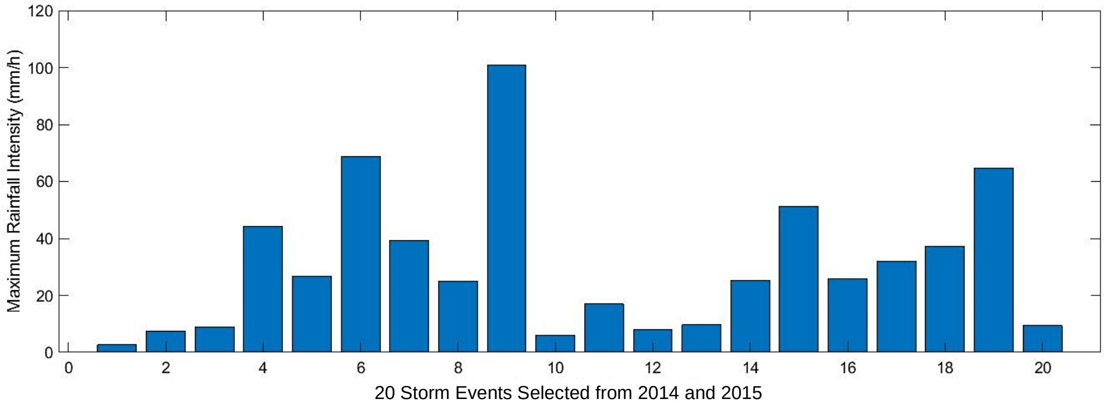

Figure 3.15 - Maximum rainfall intensity for each storm event selected from 2014 and 2015.

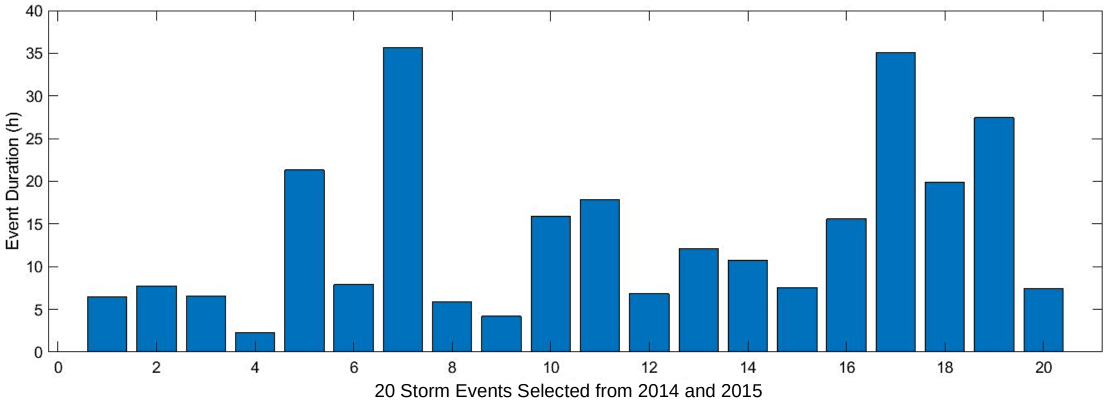

Figure 3.16 - Duration of each storm event selected from 2014 and 2015.

Similar to the model calibration, the heterogeneity of events is important to analyze the performance of the control procedures and account for different scenarios in the sewer system.

The statistical difference between the reference and RTC scenarios is determined using a two sample K-S test, as described in subchapter 3.3. This test was performed in MATLAB software where the result of h is 1 if the null hypothesis at the 5% significance level is rejected, and 0 otherwise. Additionally, the p-value, ranging from 0 to 1, was determined and it indicates if there is a large deviation from the normal distribution in the two samples (i.e., low p-value), meaning the null hypothesis is rejected, or a low deviation (i.e., high p-value). The results obtained are presented and discussed in Chapter 4.

4. Results and Discussion

4.1. Calibration

As described in Chapter 3, the model was calibrated through the adjustment of the parameters, presented in Table 3.4, and validated through the analysis of the NSE coefficient values obtained from the comparison between the model derived flow and the monitoring data. Following numerous simulations, the fraction volume (f_on) value defined for each catchment upstream of the pumping station Aalst is 0.05. This value is only different for the PS Aalst, where it was determined as 0.40. This parameter has proven to work best in this pumping station as it atones for the slow operation of the pump, and it allows the release of a higher volume of water towards the downstream of the system. As for the upstream catchments, this parameter did not significantly influence the results, thus the standard value for this fraction (0.05) was preserved.

Regarding the maximum depression storage for impervious areas, the parameter value for all the municipalities upstream of the PS Aalst was changed to 5 mm. Since this parameter accounts for the maximum water storage in depressions on the soil surface at the onset of a storm event, which alters the runoff and it is difficult to measure, this amount of water is discarded of simulations to avoid overestimating the runoff volume.

The values selected for these parameters, particularly f_on, can depend on seasonality, where the model results tend to be less accurate towards the end of the year (Table 4.1). This decrease in accuracy is mainly caused by an overestimation of the outflow volume in these catchment areas but determining the reason for this was considered beyond the scope of this dissertation. Nonetheless, a stable and reasonable resemblance between the model simulation and measurement data was achieved. Since no further improvements were obtained, the calibration performed using 24 iterations was considered sufficient. The NSE results of the final and definitive simulation are shown in the Table 4.1, for each of the 15 events presented in subchapter 3.4.4 and the two monitoring locations (i.e., PS Aalst and CS De Meren).

Table 4.1 – Nash-Sutcliffe Efficiency coefficient values for the selected storm events of 2019.

Storm Events (dd – mm)	**PS Aalst**	**CS De Meren**
19 May to 20 May	0.76	0.37
28 May	0.61	0.44
4 June to 5 June	0.74	0.70
12 June	0.57	0.38
12 July	0.14	0.16
27 July	-1.65	0.34
9 August	0.77	0.54
29 August	0.81	0.25
1 October	0.72	0.56
4 October	0.45	0.27
16 October	0.63	-0.10
3 November	0.19	-0.02
27 November	0.15	-0.45
12 December to 13 December	-0.19	0.28
21 December to 22 December	0.43	-0.03

The analysis of the results presented in Table 4.1 allows to verify that the model is better calibrated for PS Aalst than CS De Meren. Nevertheless, both of these monitoring locations have a majority of NSE coefficient values above 0, for the selected storm events, meaning that the model simulated data is potentially more accurate in predicting flow in the system than the mean value of the monitoring data. For PS Aalst, the median NSE value is 0.57 and the minimum and maximum are -1.65 and 0.81, respectively. As for CS De Meren, the median is 0.28 and the minimum and maximum are -0.45 and 0.70, respectively. The median values are reported instead of means because the latter are more sensitive to extreme values. The low NSE values are mainly obtained for storm events with low total rainfall depths, where the outflow volume in these catchment areas is overestimated. This indicates that this model seems to be better calibrated for storm events with high total rainfall depths. Based on the performance ratings presented in Table 3.1, the median value obtained for PS Aalst can be considered satisfactory, but, for CS De Meren, the median value is unsatisfactory. This can be explained by the wrong assumption that CS De Meren is continuously operating at a maximum effluent flow rate of 5000 m^3/h which can be adjusted by human operators, making this analysis more difficult.

An important aspect for this study that these results do not demonstrate is the timing of these storm events which is crucial for control implementation. A comparison between the start time of storm events of the model simulated and monitoring data is shown in Figure 4.1, for CS De Meren and PS Aalst. For this, the start of a storm event was defined when the effluent flow rate at these locations raised rapidly above 2000 m^3/h.

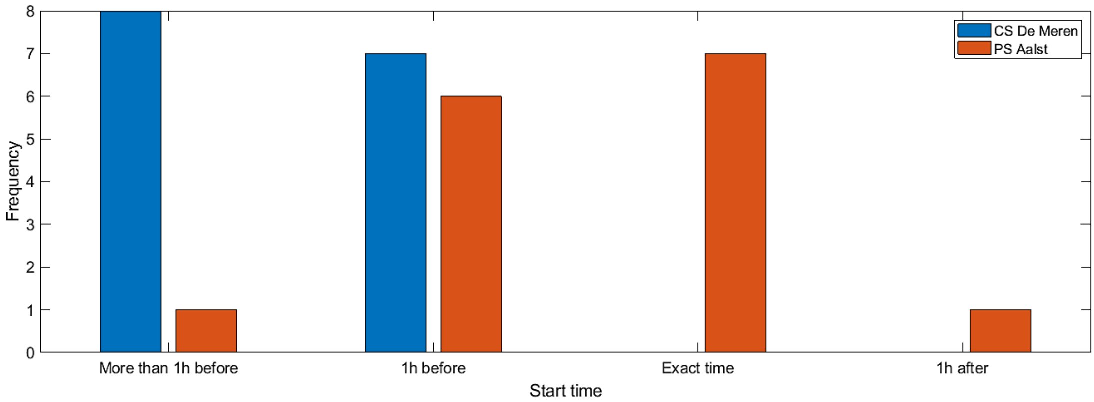

Figure 4.1 – Comparison between the start time of storm events of the model and monitoring data.

The start time of the storm events was identical between the model simulated and monitoring data only for PS Aalst, for approximately 47% of the events. Both for CS De Meren and PS Aalst, the model simulated data generated these storm events one hour before the monitoring data, for 47% and 40% of the events, respectively. The rest of the occurrences started more than one hour before the monitoring data for CS De Meren, for approximately 53% of the events. For PS Aalst, one of the last two events started more than one hour before and other started one hour later.

Based on these results, the start time of the storm events tends to be at least one hour before the monitoring data for both locations. Even though the exact time would be preferable, having the storm events start slightly earlier and effluent flow rates generated before the monitoring data should not affect the simulations intended for this study. The timing of the storm events is considered acceptable.

From a practical point of view, these results are subject to a relatively large amount of uncertainty, as no uncertainty analysis was performed because it was beyond the scope of this dissertation. However, it allows to establish that the model dynamics are sufficiently calibrated for this section of the system, as the general visual agreement between simulated and observed data indicates adequate calibration and validation (Singh et al., 2004). Moreover, as stated in the Chapter 3, the remnant part of the Eindhoven system was assumed to be sufficiently calibrated, by the previous model users (i.e., Moreno-Rodenas et al., 2019), for the model simulations required in this study.

4.2. Accuracy of the forecast data

The main issue of applying radar rainfall forecast in a model is the uncertainty of the data compared with the observed rainfall that will consequently lead to inaccurate flow predictions in the system. As described in subchapter 3.4.5.3, to mitigate this issue, a binary approach was applied to the real radar rainfall forecast, where the value 1 is assumed when a particular threshold is exceeded and the value 0 for the opposite. This was tested for five different total rainfall depth thresholds, where the value 1 was only assumed if the maximum value of total depth forecasted over a two-hour horizon exceeded these established thresholds.

A comparison between this binary real forecast and perfect forecast was performed using a contingency table to assess the accuracy of the real forecast compared with the observed data. In Tables 4.2 and 4.3, this comparison is presented for the catchment areas of Riool Zuid and Eindhoven Stad, based on the total rainfall depth threshold of 0.01 mm and the 20 storm events selected from 2014 and 2015.

Table 4.2 – Comparison between binary real forecast and perfect forecast (threshold of 0.01 mm) for Riool Zuid.

		Observed	
		Yes	No
Forecast	Yes	4389 (37.21%)	1407 (11.93%)
	No	3228 (27.37%)	2770 (23.49%)

Table 4.3 - Comparison between binary real forecast and perfect forecast (threshold of 0.01 mm) for Eindhoven Stad.

		Observed	
		Yes	No
Forecast	Yes	3422 (29.01%)	1407 (11.93%)
	No	2594 (21.99%)	4371 (37.06%)

For the catchment area of Riool Zuid, the binary real forecast correctly predicts the “yes” and “no” storm occurrences (i.e., hits and correct negatives) for approximately 61% of the total events. This value is slightly higher for Eindhoven Stad, where the hits and correct negatives represent 66% of the total events. The incorrect predictions (i.e., misses and false alarms) range from 34% to 39% for the two catchment areas. These predictions need to be considered and evaluated to determine its impacts on the control implementation and the urban drainage system.

Considering the other four total rainfall depth thresholds (i.e., 0.50, 1.00, 2.50 and 5.00 mm), the comparison between these binary real and perfect forecasts was also assessed for the two catchment areas and the same storm events. Figures 4.2 and 4.3 present the evolution of correct and incorrect predictions obtained for the five thresholds and the previous catchment areas and storm events.

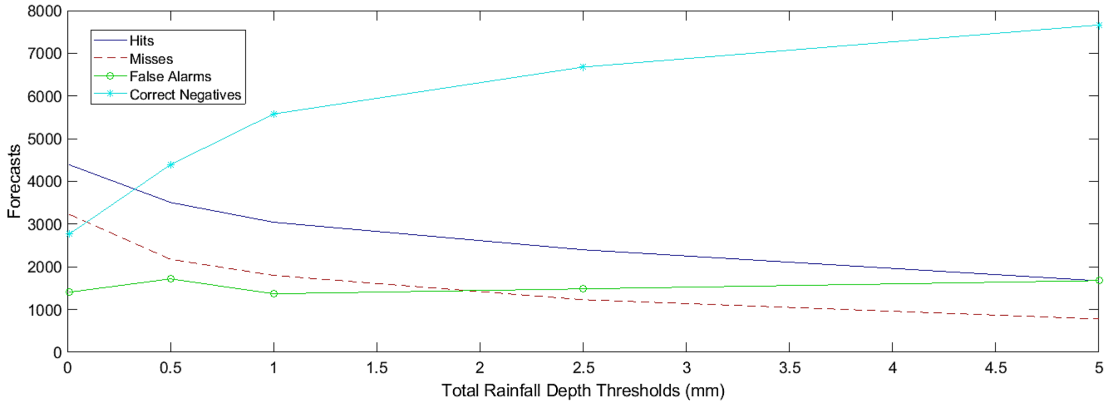

Figure 4.2 - Comparison between binary real forecast and perfect forecast for Riool Zuid.

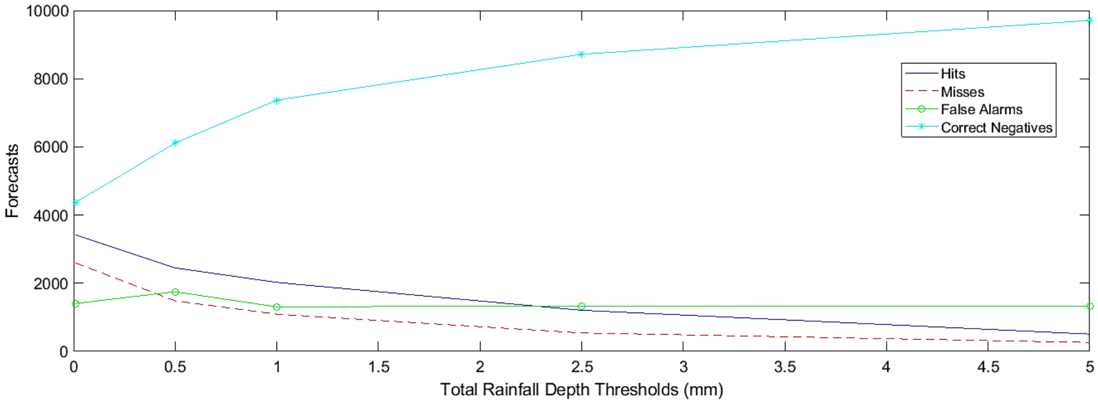

Figure 4.3 - Comparison between binary real forecast and perfect forecast for Eindhoven Stad.

The correct predictions increased from threshold 0.01 mm to 5.00 mm, reaching values of approximately 79% and 87%, for the catchment areas Riool Zuid and Eindhoven Stad, respectively. As for the incorrect predictions, the values decreased, ranging from 13% to 21% for the two catchment areas.

However, it is noticeable that the improvement in the correct predictions is due to the increase of correct negatives, and not the hits, which decrease from threshold 0.01 mm to 5.00 mm. This decrease ranges from 23% to 25%, for the two catchment areas. The incorrect predictions present a decrease of approximately 18% to 21%, mainly due to the decrease of misses. The false alarms increase slightly for the threshold of 0.50 mm, but, overall, these remain stable.

Since a higher total rainfall depth threshold leads to the negation of numerous storm events, the increase of correct negatives and decrease of hits and misses can be expected. The fact that the false alarms remain stable with the increase of the thresholds might indicate that the binary real forecast is falsely predicting storm events where the maximum total rainfall depth is above 5.00 mm.

The POD, FAR and POFD were calculated to better understand the performance of each threshold. In Table 4.4, the results obtained for these verification statistics are summarized for each threshold and catchment area.

Table 4.4 – Verification statistics for the five thresholds and the two catchment areas.

Catchment Area	Threshold (mm)	POD (%)	FAR (%)	POFD (%)
	0.01	57	29	24
	0.50	62	42	22
Eindhoven Stad	1.00	65	39	15
	2.50	69	52	13
	5.00	66	72	12
	0.01	58	24	34
	0.50	62	33	28
Riool Zuid	1.00	63	31	20
	2.50	66	38	18
	5.00	68	50	18

These results demonstrate that the POD and FAR values tend to increase with higher total rainfall depth thresholds for both Eindhoven Stad and Riool Zuid. As for the POFD, the values decrease with the increase of these thresholds. The maximum POD values range from 66% to 69% for the thresholds of 2.50 and 5.00 mm, which means that opting for one of these thresholds allows to correctly predict more than 66% of the storm occurrences. The observations drawn previously indicated that both hits and misses decrease with higher thresholds, due to the negation of more storm events. These POD results show that the ratio of hits to the total number of observed storm events increases with higher total rainfall depth thresholds, which seems to indicate that considering these thresholds might increase the accuracy of the predictions.

However, these thresholds also lead to higher values of FAR, which can range from 50% to 72%. These FAR values are unfavorable because it means the false alarms represent more than 50% of the “yes” forecasts due to the decrease of hits. As for POFD, for the total of “no” storm occurrences, less than 34% represent false alarms related to the forecast and these values tend to decrease with higher thresholds due to the increase of correct negatives.

Following this logic, the preferable solution should be a threshold that leads to a high POD value and low FAR and POFD results, for both catchments. The closest fit to this description would be the threshold of 1.00 mm, that leads to a reasonable POD value, ranging from 63% to 65%, while decreasing the FAR (i.e., 31% to 39%) and POFD (i.e., 15% to 20%) values. This is not conclusive to determine which threshold should be considered, the five that were established need to be tested in the model simulations, particularly, to evaluate the risks related with the false alarms and misses associated with the forecast.

4.3. Control Implementation

4.3.1. CSO volume

The binary perfect forecast, presented in subchapter 3.4.5.3, was applied to the two control strategies (i.e., control strategy 1 and control strategy 2) to analyze and validate their performance on CSO volume reduction, while avoiding the overcharge of the WWTP. The total CSO volume obtained using the perfect forecast with the threshold of 0.01 mm is compared and presented in Figure 4.4, for the reference scenario (i.e., control off) and control strategies 1 and 2 and the time interval of 2014 and 2015. Additionally, five relevant CSO and overflow locations were selected to interpret the differences in total CSO volume for the three control scenarios.

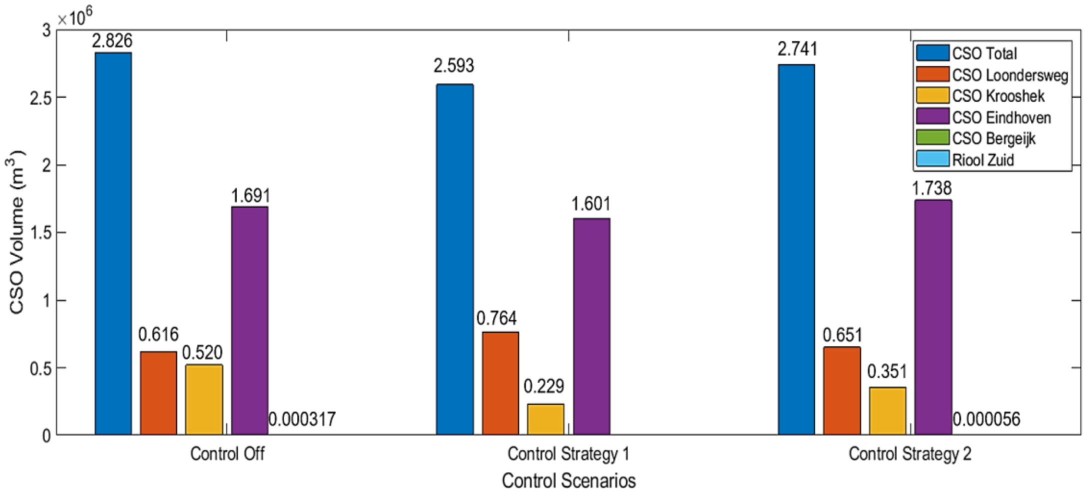

Figure 4.4 – Total CSO volume obtained for the different control scenarios in 2014 and 2015.

Comparing these two strategies with the control off scenario, control strategy 1 is the scenario with the highest total CSO volume reduction, of approximately 8%. This decrease of CSO volume occurred at CSOs Bergeijk, Eindhoven and Krooshek, where the volume was reduced by approximately 100%, 5% and 56%, respectively. This volume minimization is obtained due to the increase of the maximum effluent flow rate allowed for each control location, based on the rainfall forecasted in a two-hour horizon. However, this strategy resulted in an increase of CSO volume at CSO Loondersweg, of approximately 24%. The major cause of this is the flow limitation at the CS De Meren, located downstream of CSO Loondersweg, which can be activated based on the existence or not of forecasted rainfall in the next two hours. As described in subchapter 3.4.5.1, the purpose of this limitation is to significantly reduce the CSO volume at CSO Krooshek, but the impacts caused by the increase of CSO volume at Loondersweg should also be determined.

The evolution of the CSO volume obtained at these five locations for control strategy 1, using perfect forecast with each of the five thresholds, is presented in Table 4.5.

Table 4.5 – CSO volume obtained for control strategy 1 using perfect forecast with each threshold.

Locations	Threshold 0.01 (m^3)	Threshold 0.50 (m^3)	Threshold 1.00 (m^3)	Threshold 2.50 (m^3)	Threshold 5.00 (m^3)
CSO Loondersweg	763 734	747 248	743 068	717 997	695 675
CSO Krooshek	228 517	253 176	257 021	280 174	278 387
CSO Eindhoven	1 600 945	1 607 537	1 616 365	1 640 172	1 719 967
CSO Bergeijk	0	3	103	102	51
Riool Zuid	0	1 474	1 627	1 984	0
CSO Total	2 593 196	2 609 439	2 618 185	2 640 429	2 694 080

Considering CSOs Krooshek, Eindhoven and Bergeijk and Riool Zuid, the CSO volume tends to increase with higher total rainfall depth thresholds, leading to a maximum increase of total CSO volume of approximately 4%. While the volume increase ranges from 7% to 18% for CSOs Eindhoven and Krooshek, respectively, new CSO events are generated at CSO Bergeijk and Riool Zuid. Since these higher thresholds negate more storm events, this control strategy has more difficulty in minimizing or preventing CSO occurrences compared with the threshold of 0.01 mm. The decrease of CSO volume at Loondersweg is explained due to less flow limitation at the CS De Meren, which is dependent on rainfall forecast information.

As for control strategy 2, the total CSO volume presents a decrease of approximately 3%, compared to the control off scenario (Figure 4.4). The CSO volume is only reduced at CSOs Bergeijk and Krooshek, leading to an improvement of 82% and 33%, respectively. For CSOs Eindhoven and Loondersweg, this strategy generated a slight increase of volume of approximately 3% and 6%, respectively. These results were obtained due to the initial flow limitation, with the objective of utilizing the spare capacity of the system and avoiding an increase of peak load at the WWTP.

Table 4.6 summarizes the evolution of CSO volume obtained for control strategy 2, using perfect forecast with each of the five thresholds.

Table 4.6 - CSO volume obtained for control strategy 2 using perfect forecast with each threshold.

Locations	Threshold 0.01 (m^3)	Threshold 0.50 (m^3)	Threshold 1.00 (m^3)	Threshold 2.50 (m^3)	Threshold 5.00 (m^3)
CSO Loondersweg	651 279	660 728	662 913	654 623	662 343
CSO Krooshek	350 878	359 254	377 485	383 861	413 025
CSO Eindhoven	1 738 309	1 775 451	1 772 241	1 790 197	1 763 064
CSO Bergeijk	56	0	46	135	47
Riool Zuid	0	0	0	0	0
CSO Total	2 740 522	2 795 433	2 812 685	2 828 816	2 838 480

Similar to control strategy 1, the total CSO volume tends to increase with higher total rainfall depth thresholds, reaching a maximum increase of approximately 3%. Considering CSOs Loondersweg, Krooshek and Eindhoven, the volume can increase by 2%, 15% and 3%, respectively. The CSO volume only variates slightly for CSO Bergeijk and remains null for Riool Zuid. Since this control strategy only maximizes the effluent flow rate when these locations are reaching full capacity and no storm event is forecasted over a two-hour horizon, the negation of storm occurrences and a delayed response from the system seem to hydraulically overcharge these locations and the downstream sections of the system.

Van Daal et al. (2017) also compared two RB-RTC scenarios to a reference scenario. One scenario (RTC CSO) aimed to reduce CSO occurrence and discharged volumes. Other (RTC WWTP) focused on limiting the maximum discharge to the WWTP without increasing CSO occurrence and discharged volumes. These scenarios were tested for only three catchments and a fourth basin that represented hypothetical transport sewer to the WWTP, and no rainfall forecasts were used, meaning that predictive control was not applied. In the case of the RTC CSO scenario, the total CSO volume was decreased by 5% for the total system, due to a slight increase of 0 – 3.8% in total CSO volume for the three catchments, which prevented the CSO events and volume in the fourth basin. The RTC WWTP scenario did not induce significant negative effects on the number of CSO events and only led to a total CSO volume increase of 1%.

To illustrate the differences between these control scenarios, the effluent and discharge (CSO) flow rates at the PS Aalst and CSO Krooshek can be observed in Figures 4.5 and 4.6. These model results were obtained for a storm event from March 29th to March 31st of 2015 using the perfect forecast with the threshold of 0.01 mm as an example.

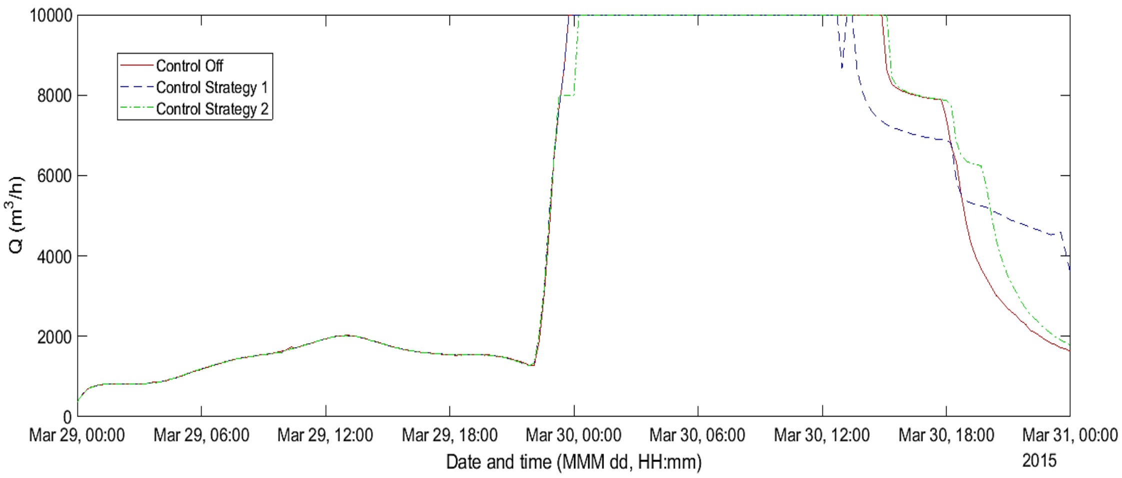

Figure 4.5 – Effluent flow rate at the pumping station Aalst on March 29th to March 31st of 2015.

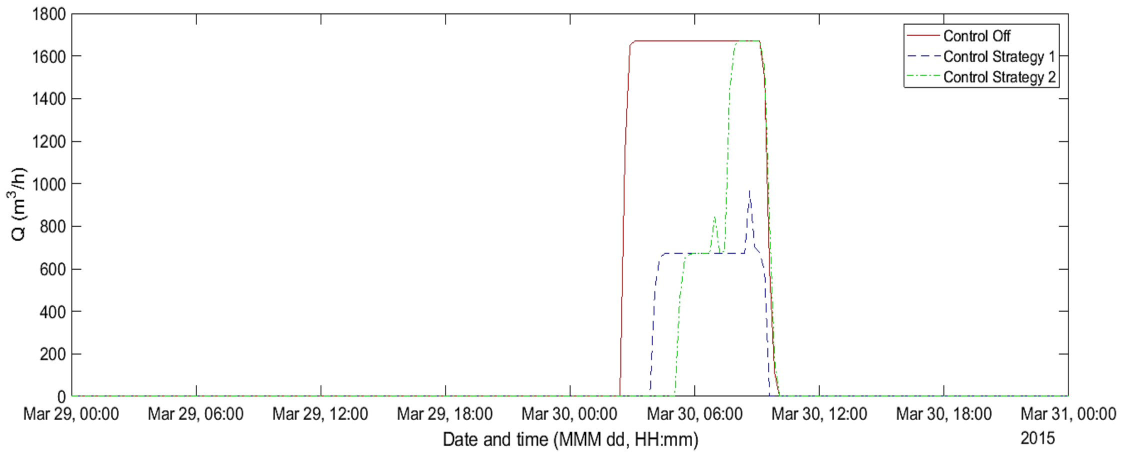

Figure 4.6 – CSO flow rate at the CSO Krooshek on March 29th to March 31st of 2015.

The effluent flow rate, presented in Figure 4.5, has a similar pattern between the scenarios, except for control strategy 1, which is reduced earlier compared to the others. The reason for this is due to the limitation of the effluent flow rate allowed by the spare capacity generated in the system. This capacity was potentially provided by the maximization of effluent flow rate at this location, two hours before the onset of the storm event. Consequently, the discharge flow rate at CSO Krooshek is also minimized, as observed in Figure 4.6.

Regarding the increase of CSO volume in Loondersweg due to the flow limitation at CS De Meren, Figure 4.7 presents the effluent flow rates at this location for the three scenarios, during March 29th to March 31st of 2015, using the perfect forecast with the threshold of 0.01 mm.

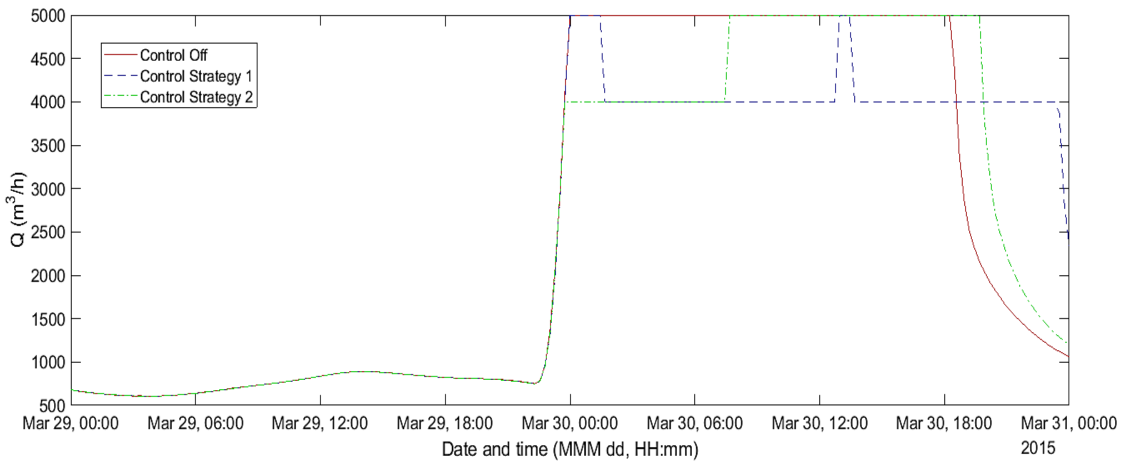

Figure 4.7 - Effluent flow rate at the control station De Meren on March 29th to March 31st of 2015.

Although, for control strategy 1, the standard value (5000 m^3/h) is set occasionally throughout the storm event, the limit value (4000 m^3/h) is predominantly used to minimize the hydraulic loading to PS Aalst and significantly reduce the CSO volume at Krooshek. The frequent activation/deactivation of actuators and rapid changes in the system should be avoided. However, these changes between the effluent flow rates do not occur intermittently during any of the storm events.

This limitation of the effluent flow rate at CS De Meren does lead to the increase of CSO volume at Loondersweg. To mitigate this element, an adjustment of the set values established for the filling degrees in the control procedures would be required. Since control strategy 2 sets the standard effluent flow rate value earlier and for a longer period, the CSO volume at Loondersweg only increases slightly, but the decrease of CSO volume at Krooshek is also less significant compared with control strategy 1.

4.3.2. WWTP

To analyze the impacts of the two strategies in the operation of the WWTP, the peak flow duration and the SST overflow volume of each control scenario were compared, based on the 20 selected storm events from 2014 and 2015, introduced in subchapter 3.4.5.3. Figure 4.8 summarizes the peak flow duration (in hours) obtained at the inlet of the WWTP, during these 20 storm events, for control off and control strategy 1 using the perfect forecast with each of the five thresholds.

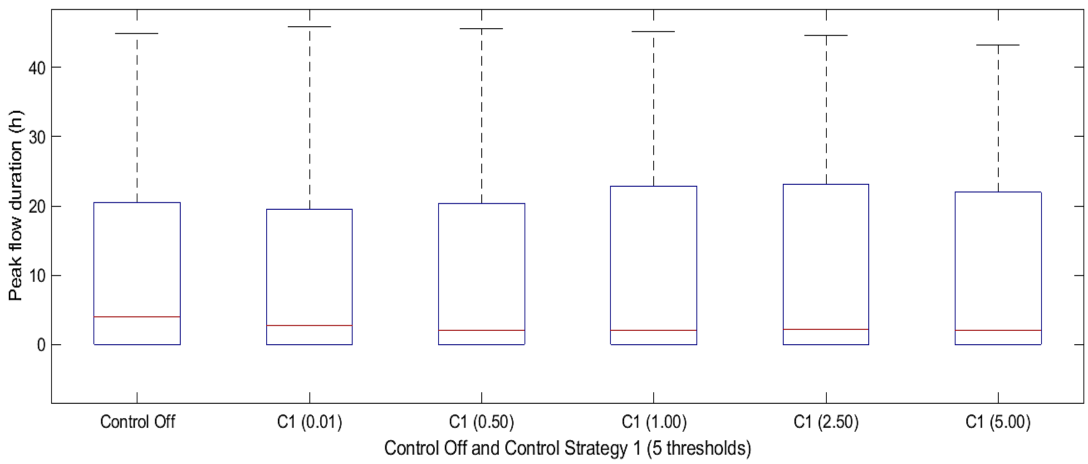

Figure 4.8 – Peak flow duration at the inlet of the WWTP for control off and control strategy 1 during the storm events from 2014 and 2015.

Compared with the control off scenario, the peak flow duration was reduced by approximately 12% for control strategy 1 with the threshold 0.01 mm. The other thresholds mainly led to a duration reduction ranging from 5% to 9%. The median event peak flow duration is slightly higher for control strategy 1 with the threshold 0.01 mm, being approximately 3h, compared with the other thresholds, which obtained a median duration of 2h.

As for control strategy 2, Figure 4.9 presents the peak flow duration (in hours) obtained at the inlet of the WWTP, during these 20 storm events, for control off and control strategy 2 using the perfect forecast with each of the five thresholds.

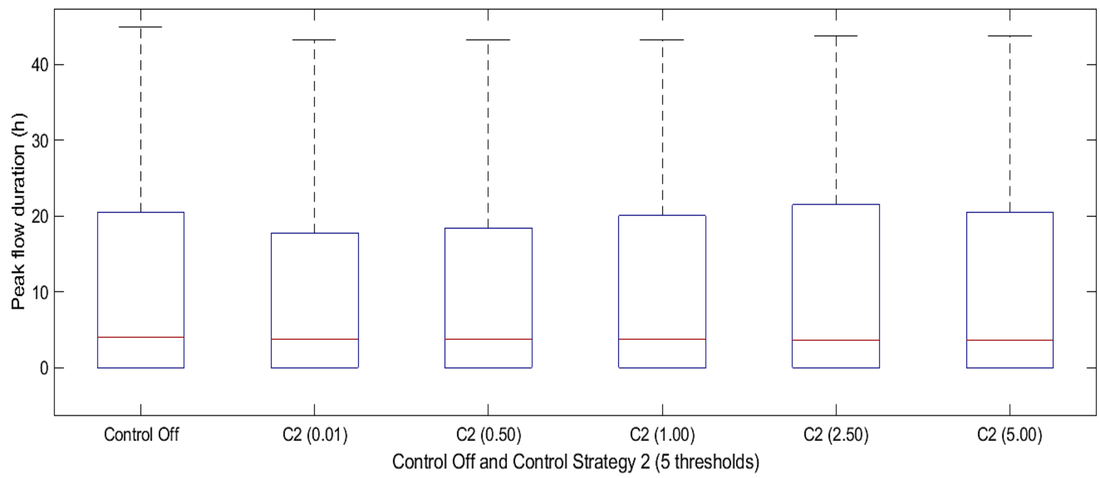

Figure 4.9 – Peak flow duration at the inlet of the WWTP for control off and control strategy 2 during the storm events from 2014 and 2015.

This strategy also reduced the peak flow duration, by approximately 18%, performing better when using the threshold of 0.01 mm. The other thresholds were able to reduce 3% to 13% of this duration. The median event peak flow duration is approximately 4h for the five thresholds.

Figure 4.10 shows an example of the influent flow pattern at the inlet of the WWTP obtained for each scenario and the storm event from March 29th to March 31st of 2015, using the perfect forecast with the threshold of 0.01 mm.

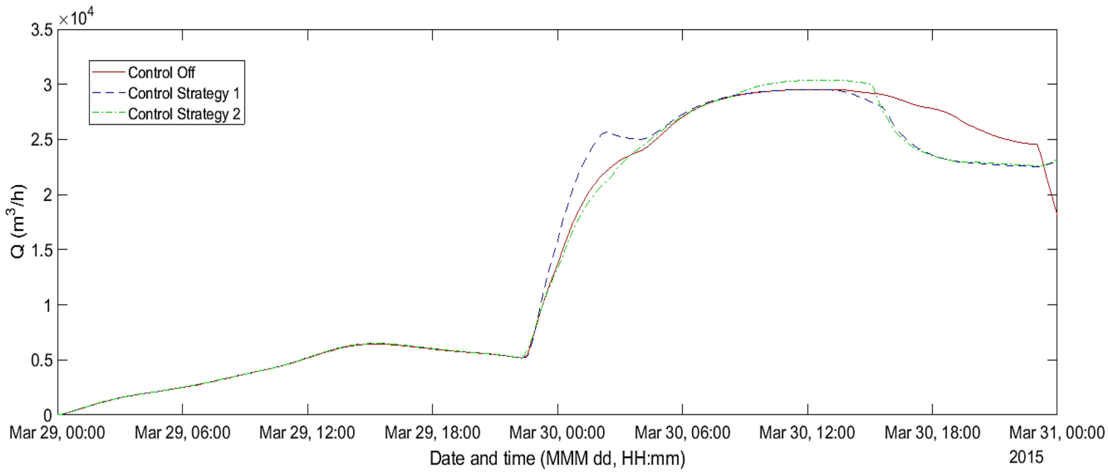

Figure 4.10 – Influent flow at the inlet of the WWTP on March 29th to March 31st of 2015.

The initial peak flow for control strategy 1, between March 30th 0:00-6:00h, resulted from the maximization of the effluent flow rates at each control location, which is activated by the expectance of rainfall over a two-hour horizon. This early response allows to derive more space in the sewer system to manage the storm events. When these events are expected to conclude in the established lead time, if there is spare capacity, the flow limitation is activated at each control location, reducing the influent flow to the WWTP and, consequently, the peak flow duration, as observed during March 30th 14:00h to March 31st 0:00h.

For control strategy 2, the influent flow pattern is similar to the control off scenario until March 30th 14:00h, where the flow is reduced earlier, like control strategy 1. Since this strategy activates flow limitation early on based on rainfall forecasted over a two-hour horizon and the spare capacity of the system, a higher peak should also be expected but delayed compared with control strategy 1. The absence of that is justified by the potential increase of CSO volume at the control locations, which allows the influent flow reduction observed during March 30th 14:00h to March 31st 0:00h.

In Figure 4.11, no apparent negative effects on the influent NH_4 load at the inlet of the WWTP are verified for both control strategies using the perfect forecast with the threshold of 0.01 mm.

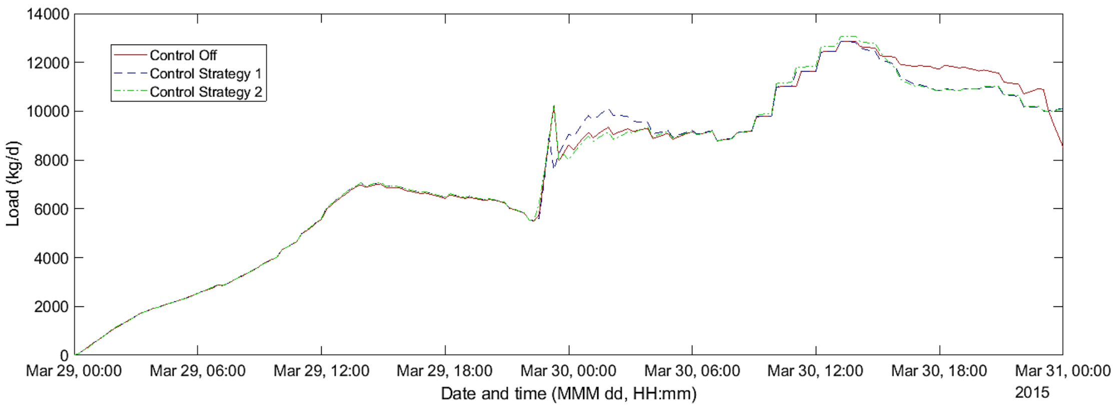

Figure 4.11 – Influent NH_4 load at the inlet of the WWTP on March 29th to March 31st of 2015.

Similarly, during March 30th 14:00h to March 31st 0:00h, the influent NH_4 load is reduced at the inlet of the WWTP for both strategies. The initial NH_4 peak obtained for control strategy 1, during March 30th 0:00-6:00h, might not have a negative effect in the effluent load, but the effluent dynamics should be assessed. However, the dynamics of the effluent parameters require further calibration with monitoring data, thus the NH_4 load at the outlet of the WWTP was not analyzed.

In terms of the influent flow and NH_4 load, the results obtained for this storm event are very similar between the two strategies, meaning that there is no further improvement by control strategy 2, which was specifically developed to avoid an increase of the peak load to the WWTP. However, it performed slightly better than control strategy 1, reducing more 6% of the peak flow duration, at the inlet of the WWTP for the 20 storm events. Nevertheless, both strategies led to the reduction of the peak flow duration and avoided overcharging the WWTP during these storm events.

Figure 4.12 presents the overflow volume obtained at the SST during the 20 storm events for control off and control strategy 1 using the perfect forecast with each of the five thresholds.

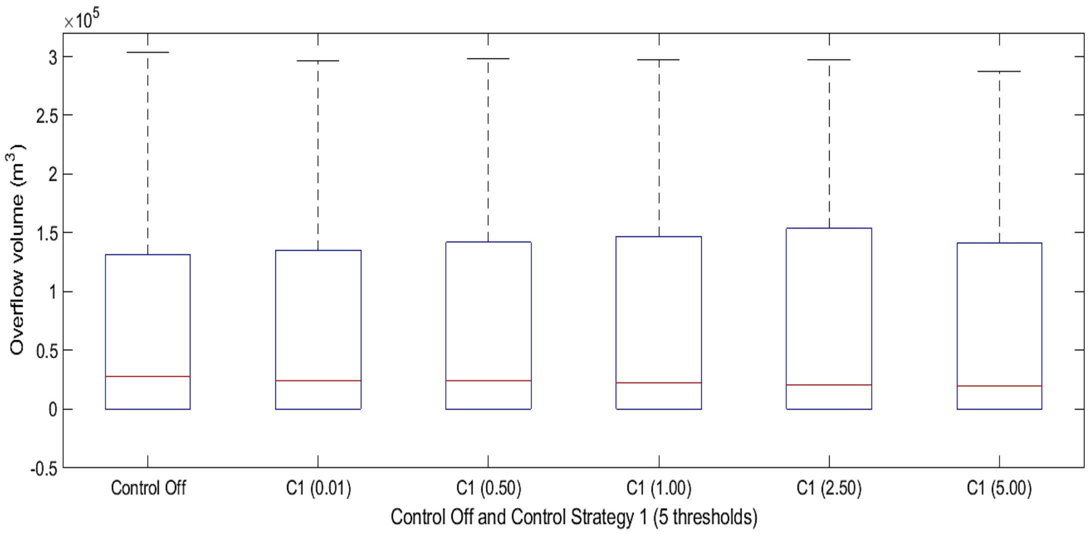

Figure 4.12 – Overflow volume at the SST for control off and control strategy 1 during the storm events from 2014 and 2015.

The overflow volume at the SST was reduced by approximately 11% for control strategy 1 using the perfect forecast with the threshold 0.01 mm. The other thresholds mainly reduced the overflow volume by 3% to 7%. The median event overflow volume is higher for control strategy 1 with the threshold 0.01 mm, being approximately 24 287 m^3, while the other thresholds can reach a minimum of 19 945 m^3.

Similarly, control strategy 2 using the perfect forecast with the threshold 0.01 mm reduced the overflow volume at the SST by approximately 11%, performing slightly better than the other thresholds, which were able to reduce this volume by 2% to 10% (Figure 4.13). The median event overflow volume is also higher for control strategy 2 with the threshold 0.01 mm, being approximately 27 348 m^3, while the other thresholds can reach a minimum of 25 641 m^3.

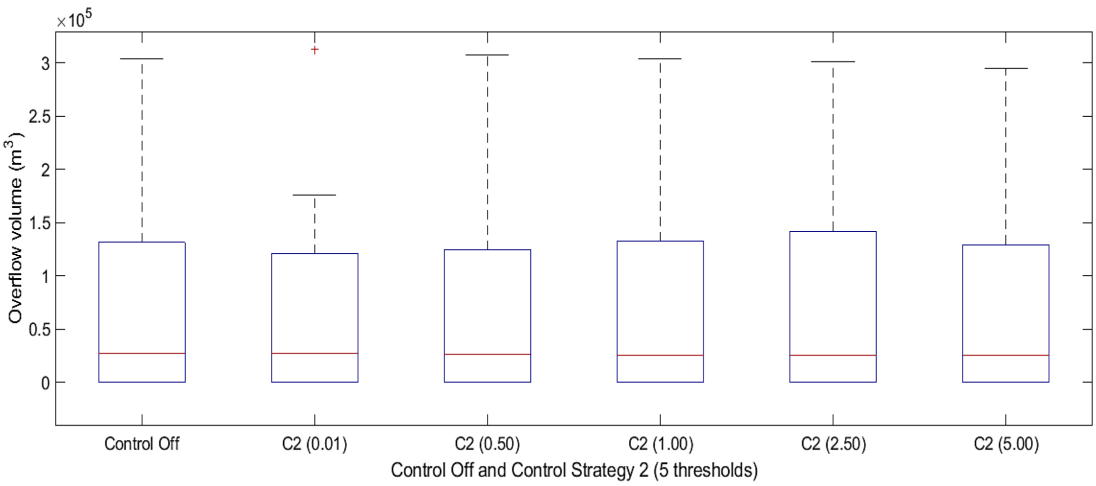

Figure 4.13 - Overflow volume at the SST for control off and control strategy 2 during the storm events from 2014 and 2015.

Since both the activation of the SST and the upstream flow transportation to the WWTP account for the rainfall forecast, the early reaction of the system is potentially contributing for this reduction of overflow volume in both strategies.

4.3.3. Perfect and Real Forecast

Following the perfect forecast results, the binary real radar forecast was applied to the two control strategies to evaluate their performance and determine the differences in using perfect and real forecast data. The total CSO volume (in m^3) is summarized in Table 4.7 for the control off scenario and control strategy 1 using perfect and real forecast with each of the five thresholds, during the previous 20 selected storm events. This total CSO volume is based on the five CSO and overflow locations selected previously in subchapter 4.3.1.

Table 4.7 – Total CSO volume for the control off and control strategy 1 (perfect and real forecast), during the storm events from 2014 and 2015.

Thresholds (mm)	Perfect Forecast (m^3)	Real Forecast (m^3)	Control Off (m^3)
0.01	1 869 401	1 905 926	
0.50	1 883 297	1 906 716	
1.00	1 899 833	1 921 666	1 950 185
2.50	1 924 434	1 933 453	
5.00	1 975 662	1 954 403	

While the CSO volume is reduced by a maximum of approximately 4% for this control strategy using perfect forecast with the threshold of 0.01 mm, the real forecast with the same threshold reduces it by approximately 2%, compared with the control off scenario. In subchapter 4.2, the POD values obtained for this threshold range from 57% to 58%, meaning that more than 57% of the total number of observed storm events are hits. Since the real forecast accurately predicts this amount of observed storm events, this could explain why the CSO volume reduced using real forecast represents approximately half of the volume reduced using the perfect forecast. The same logic seems to apply for the next three thresholds (i.e., 0.50, 1.00 and 2.50 mm), where the POD values range from 62% to 69% and the CSO volume reduced using real forecast represents more than 60% of the volume reduced using the perfect forecast.

The total CSO volumes tend to increase for the higher total rainfall depth thresholds, but only the perfect and real forecasts with the threshold 5.00 mm slightly increase the CSO volume, by approximately 0.2% and 1%, above the volume obtained for the control off scenario. For this threshold, the perfect forecast led to a larger total CSO volume than the real forecast. The higher total rainfall depth thresholds increase the ratio of hits to the total number of observed storm events, but, as more storm events are negated, the number of hits also reduces. This also leads to an increase of the ratio of false alarms to the total of “yes” forecasts. The real forecast performed better than the perfect forecast for the threshold of 5.00 mm potentially due to the negation of more observed storm events by the perfect forecast. Some of the observed storm events negated by the perfect forecast might have been considered “false alarms” associated to the real forecast, leading to the results obtained for this threshold.

Considering the peak flow duration at the inlet of the WWTP, control strategy 1 using perfect and real forecasts managed to reduce it, compared with the control off scenario (Table 4.8).

Table 4.8 – Peak flow duration for the control off and control strategy 1 (perfect and real forecast), during the storm events from 2014 and 2015.

Thresholds (mm)	Perfect Forecast (h)	Real Forecast (h)	Control Off (h)
0.01	203	215	
0.50	210	215	
1.00	216	220	231
2.50	231	219	
5.00	220	220	

While the perfect forecast with the threshold of 0.01 mm reduces the peak flow duration by 12%, the real forecast with the threshold of 0.01 mm manages to reduce it by 7%. Similarly, the peak flow duration reduced using the real forecast represents approximately 58% of the reduction obtained for the perfect forecast. This would suggest that the POD values could justify the results obtained for the forecasts with this threshold. The peak flow duration also tends to increase with higher total rainfall depth thresholds for both forecasts. However, for these thresholds, the results obtained for the real forecast and perfect forecast are not consistent with the POD values.

Compared with the control off scenario, control strategy 2 increased the total CSO volume by approximately 2% and 3%, using both perfect and real forecast with the threshold of 0.01 mm, respectively (Table 4.9). This CSO volume also tends to increase with the higher total rainfall thresholds.

Table 4.9 - Total CSO volume for the control off and control strategy 2 (perfect and real forecast), during the storm events from 2014 and 2015.

Thresholds (mm)	Perfect Forecast (m^3)	Real Forecast (m^3)	Control Off (m^3)
0.01	1 995 043	2 007 402	
0.50	2 014 241	2 008 826	
1.00	2 017 513	2 013 102	1 950 185
2.50	2 046 404	2 012 689	
5.00	2 012 763	2 024 234	

The main objective of this strategy is not reducing CSO volume, but, rather, avoid additional CSO volume. These results show that control strategy 2 is not able to prevent additional overflow volume due to the initial flow limitation at the control locations, two hours before the onset of a storm event. This would imply that by negating more storm events, there would be less flow limitation and less CSO volume with the increase of the total rainfall depth thresholds. However, as it was stated in subchapter 4.3.1, the negation of storm events and the increase of the filling degree upstream of the control locations generated by these events can lead to a more frequent maximization of the effluent flow rate. This maximization and the delayed response of the system also seems to hydraulically overcharge these locations and the downstream sections of the system, which tends to increase the total CSO volume for these storm occurrences.

When using the perfect and real forecasts with the threshold of 0.01 mm, this strategy seems to balance the limitation and maximization of effluent flow at the control locations, leading to a smaller increase of CSO volume compared with the other thresholds. For the thresholds of 0.50, 1.00 and 2.50 mm, the total CSO volumes are lower using real forecast. This means that the observed storm events that are negated by the perfect forecast from the threshold 0.01 mm to these three thresholds generates an imbalance between the limitation and maximization of effluent flow at the control locations, compared with the real forecast. This is not verified for the threshold of 5.00 mm, because the negation of more storm events by the perfect forecast must have reduced the flow limitation while the “false alarms” associated to the real forecast activated and increased this limitation.

The peak flow duration was also reduced by the control strategy 2 using both forecasts, compared with the control off scenario (Table 4.10). For this strategy, the peak flow duration also tends to increase with higher total rainfall depth thresholds.

Table 4.10 - Peak flow duration for the control off and control strategy 2 (perfect and real forecast), during the storm events from 2014 and 2015.

Thresholds (mm)	Perfect Forecast (h)	Real Forecast (h)	Control Off (h)
0.01	190	202	231
0.50	201	205	
1.00	206	212	
2.50	225	213	
5.00	222	217	

The perfect forecast with the threshold 0.01 mm reduces the peak flow duration by 18%, while the real forecast reduces it by 13%. Similar to control strategy 1, the results obtained for these forecasts are not consistent with the POD values. The real forecast only performs better than the perfect forecast for the thresholds of 2.50 and 5.00 mm, potentially due to “false alarms” associated to the real forecast that might correspond to observed storm events negated by the perfect forecast.

The performance of control strategy 1 was reduced when using real forecast due to less observed storm events accurately predicted by this forecast, which can be expected. However, both perfect and real forecasts allowed control strategy 1 to achieve its objective and to reduce CSO volume, compared with the control off scenario. The false alarms associated to the real forecast did not seem to hinder the performance of this strategy and these might have improved the total CSO volume obtained for the threshold of 5.00 mm. This strategy was also able to reduce the peak flow duration at the inlet of the WWTP using both of the forecasts.

The increase of CSO volume obtained for control strategy 2 resulted from the control procedures developed and not, particularly, the forecasts used. This could be expected because the main objective was not reducing CSO volume, but, rather, reduce the peak flow duration at the inlet of the WWTP. Although, this strategy managed to reduce it using both forecasts, it did not show further improvement compared with control strategy 1.

4.3.4. Correlation with Rainfall Characteristics

The rainfall characteristics of the storm events, such as total rainfall depth and maximum rainfall intensity, influence the amount of CSO volume generated in the system. Therefore, analyzing the performance of the control strategies based on these characteristics is also essential.

For this, the correlation between the total rainfall depth and maximum rainfall intensity and the total CSO volume obtained for the control off scenario and control strategies 1 and 2 was analyzed, during the 20 storm events from 2014 and 2015. Since the results for each control strategy are similar for both forecasts (i.e., perfect and real), the control strategies using perfect forecast with the threshold of 0.01 mm were selected for this evaluation. Figure 4.14 presents the correlation between the total CSO volume, obtained for the three scenarios, and the total rainfall depth, during the storm events from 2014 and 2015.

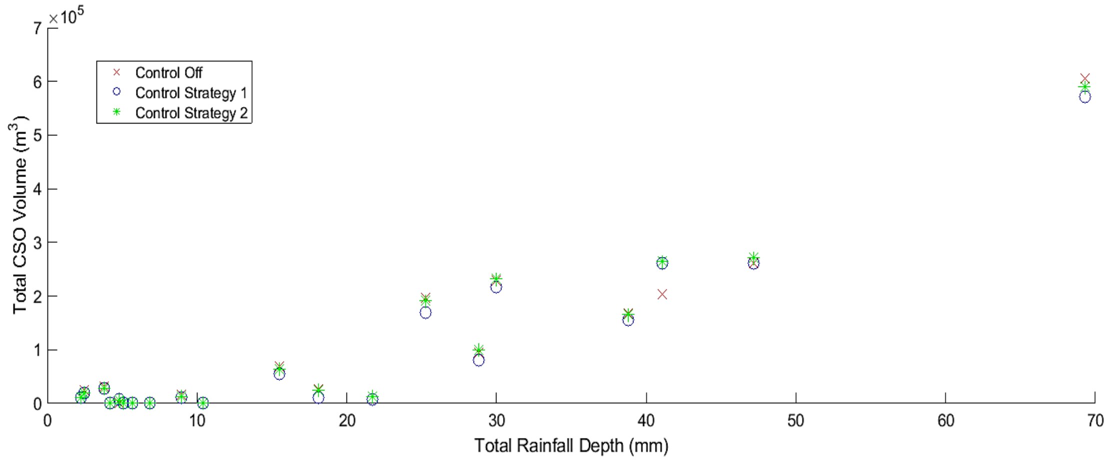

Figure 4.14 - Correlation between the total CSO volume and the total rainfall depth, during the storm events from 2014 and 2015.

When the total rainfall depth of the storm events is above 10 mm, the total CSO volume varies slightly between the control off and the control strategies. This variation is more noticeable for control strategy 1 and it mostly consists in CSO volume reduction. For the other thresholds, the same variation is also observed, but it is smaller when compared with the threshold of 0.01 mm.

In Figure 4.15, the correlation between the total CSO volume, obtained for the three scenarios, and the maximum rainfall intensity, during the storm events from 2014 and 2015, is summarized.

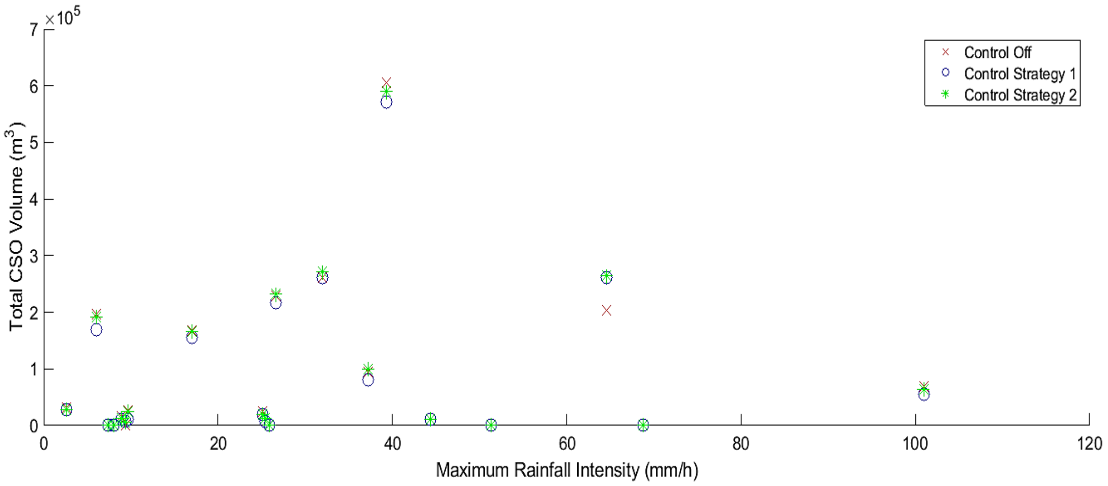

Figure 4.15 - Correlation between the total CSO volume and the maximum rainfall intensity, during the storm events from 2014 and 2015.

Comparing the control off and the control strategies, only control strategy 1 is able to slightly reduce the CSO volume obtained during storm events with maximum rainfall intensities below 40 mm/h. This variation is also smaller for the other thresholds when compared with the threshold of 0.01 mm.

In summary, control strategy 1 has a better performance for storm events with total rainfall depths above 10 mm and maximum rainfall intensities below 40 mm/h. The benefits of this strategy are more noticeable for storm events with high total rainfall depths, because these lead to higher volumes of water in the system that are promptly transported to the WWTP, to generate more space capacity. Contrarily, storm events with low total rainfall depths do not benefit in the same manner, as there is not sufficient volume to trigger the heuristic rules developed. As for control strategy 2, no significant variations are observed for these rainfall characteristics.

4.3.5. Statistical Significance Analysis

In subchapter 4.3.3, it was determined that the performance of the control strategies can be reduced when applying real forecast, but the objectives can still be achieved. To confirm if the use of the perfect forecast is significantly different than the use of the real forecast, a statistical significance analysis of the generated model data was performed. This analysis consisted in a two sample K-S test, that allowed to determine if two different sets of data, related to the total CSO volume obtained for each control strategy and forecast, belong to the same continuous distribution. To clarify, control strategy 1 (C1) using perfect forecast (PF) was compared with this same strategy applying the real forecast (RF) and the control off scenario (Off). The perfect forecasts were only compared with the real forecasts with the same thresholds, for the 20 selected storm events from 2014 and 2015. Similarly, this approach was applied to control strategy 2 (C2).

The analysis of the K-S test results leads to the conclusion that there is no statistically significant difference between the control scenarios (Table 4.11).

Table 4.11 - K-S test results for the different control strategy 1 and 2 scenarios, during the storm events from 2014 and 2015.

Thresholds	C1 (PF) and Off		C1 (PF and RF)		C2 (PF) and Off		C2 (PF and RF)	
(mm)	h	p-value	h	p-value	h	p-value	h	p-value
0.01	0	0.9655	0	0.9655	0	0.9999	0	0.9999
0.50	0	0.7710	0	0.9999	0	0.9999	0	0.9655
1.00	0	0.9655	0	0.9999	0	0.9999	0	0.9999
2.50	0	0.9999	0	0.9999	0	0.9999	0	0.9999
5.00	0	0.9655	0	0.9999	0	0.9999	0	0.9999

Since the h values for all scenarios are equal to 0, the null hypothesis that these sets of model data belong to the same normal distribution is not rejected, for a significance level of 5%. Consequently, these sets of data also present a high p-value, ranging from 0.7710 to 0.9999, which means that there is a low deviation from the normal distribution. This is true for all the scenarios evaluated, including the control off scenario, meaning that there is no statistical benefit in applying these control strategies to the standard functioning of the system.

4.4. Summary

The results, presented in this Chapter, allow to respond to the four sub questions of this dissertation. The first sub question was related with the possibility of an IUDS model delivering accurate results. In response to this, the analysis of the calibration results and the NSE values obtained demonstrate that the Eindhoven's full-integrated catchment model is able to deliver a general visual agreement between the model derived flow and the observed data and an acceptable timing of the storm events.

When investigating the accuracy of the radar rainfall forecast data compared with observed rainfall data, the real radar rainfall forecast is considered accurate, as it correctly predicts a considerable amount of storm occurrences, above approximately 61%, in the system.

The combination of rainfall data and heuristic control strategies proves to be beneficial for the performance of the Eindhoven system, as it contributes for CSO volume reduction while avoiding the overcharge of the WWTP. This description is fit for control strategy 1, as control strategy 2 only performed better than the reference scenario, by reducing the peak flow duration at the inlet of the WWTP. In terms of avoiding additional overflow volume, it succeeded for the entire year period, but not the 20 storm events selected from the time interval of 2014 and 2015. The use of this strategy resulted in no further improvement compared with control strategy 1. Both control strategies slightly increased the CSO volume at Loondersweg, which can also be a risk for the quality of the receiving watercourses. For this, the quality of these watercourses should also be addressed.

The performance of the control strategies was mainly reduced when applying real forecast, due to less observed storm events accurately predicted. However, the main objectives of these strategies were still achieved. The increase of the total rainfall depth thresholds leads to the negation of observed storm events, which also hinders the performance of the control strategies. The false alarms associated to the real forecast did not seem to affect negatively the results, and, for some thresholds (e.g., 5.00 mm), it potentially enhanced the results. It was also concluded that there is no statistically significant difference between the reference scenario and the two control approaches using both forecasts.

Although the binary real forecast data needs further improvement, it has the potential to enhance the performance of the urban drainage systems, as it provides early information about the storm events and adjustment of the actuators to manage these occurrences.

The trade-off between the benefits and risks was not assessed and it needs further investigation, but there is true potential in applying binary radar rainfall forecast in RB-RTC.

Volume-based RB-RTC with binary radar rainfall forecast data can potentially enhance the performance of heuristic control in the urban drainage systems and be improved, through control design and adjustment of a set of rules and values, to minimize the risks presented previously.

5. Conclusions

This dissertation assessed the potential of combining real radar rainfall forecast with rule-based real time control (RB-RTC) of integrated urban drainage systems (IUDS) to determine if this could enhance the performance of heuristic control. Despite a number of studies have used rainfall forecasts aiming to improve the control efficiency of real time control (RTC) strategies, only one paper was reported to investigate the use of authentic rainfall forecast with RTC, but it was applied to optimization-based control.

Therefore, the main research question was: Can the use of rainfall forecast enhance heuristic control in IUDS? The sub questions focused on the viability of IUDS model results, the accuracy of radar rainfall forecast data and the benefits and risks of the control implemented.

The Eindhoven's IUDS was selected as the case study due to its suitability for control implementation and the existence of a full-integrated catchment model developed for this system. To evaluate if this model could deliver accurate flow results compared with monitoring data, it was calibrated through the adjustment of two model parameters and validated based on Nash-Sutcliffe Efficiency (NSE) coefficient values. The real radar rainfall forecast was processed in a binary approach and later compared with observed rainfall data using verification statistics to determine its accuracy. Based on model simulations, the potential of heuristic predictive control was explored through the implementation of two volume-based control strategies with binary perfect and real rainfall forecasts. Both strategies aimed at reducing combined sewer overflows (CSO) volume and the peak flow duration at the wastewater treatment plant (WWTP).

Based on the calibration results and NSE values obtained, the performance rating for one of the monitoring locations was considered unsatisfactory due to an uncertain assumption of the operation of this control station. However, the model demonstrated a satisfactory performance for the other monitoring location, an acceptable timing of the storm events and delivered a general visual agreement between the model derived flow and the observed data. This information leads to the conclusion that the Eindhoven's full-integrated catchment model is sufficiently calibrated and validated and it is able to deliver viable results for this study.

When investigating the accuracy of the real radar rainfall forecast data applied in this study, this binary forecast is considered accurate compared with observed data, as approximately 61% to 87% of the predicted results are true. This accuracy increases for higher total rainfall depth thresholds (e.g., 5.00 mm). These thresholds also lead to an increase of the probability of detection (POD) values, meaning it correctly predicts more storm occurrences than it misses. This would indicate that higher total rainfall depth thresholds, such as 5.00 mm, are preferable due to higher values of POD, but the false alarm ratio (FAR) values also increase, meaning that there are more false alarms. Since there was not a statistically significant difference in using any of the five thresholds for the two control strategies, there is not an optimum threshold for this particular case study. Nonetheless, both control strategies performed better using the binary forecast with the smallest threshold, 0.01 mm, and this would be preferable, as it simultaneously leads to high POD and low FAR and POFD results.

The combination of rainfall data and heuristic control strategies was evaluated based on the total volume of CSO events and the peak flow duration of the WWTP. Regarding both strategies, the best results were obtained through the control strategy 1 that focused in providing space in the sewer system and using the WWTP at maximum capacity, based on the rainfall forecasted over a two-hour horizon. While it managed to minimize total CSO volume, particularly for storm events with high total rainfall depths, it also avoided a significant additional overflow volume and an increase of the peak load at the inlet of the WWTP. However, it slightly increased the CSO volume at Loondersweg, which can constitute a risk for the quality of the receiving watercourses.

The performance of these strategies was mainly reduced when applying real forecast, due to less observed storm events accurately predicted, but their main objectives were still achieved. This performance was also hindered when using both forecasts with higher total rainfall depth thresholds, as these lead to the negation of more observed storm events, which supports the use of a smaller total rainfall depth threshold. It was also concluded that there is no statistically significant difference between the standard functioning of the system (i.e., reference scenario) and the two control strategies implemented.

The binary real forecast data might need further improvement, but it has the potential to enhance the performance of the urban drainage systems, as it provides early information about the storm events and adjustment of the actuators to manage these occurrences.

Even though the trade-off between these benefits and risks was not assessed and further investigation is still required, this approach of applying binary forecast data proved to be beneficial for the performance of the Eindhoven's system.

This study demonstrates that the application of binary radar rainfall forecast in RTC can potentially enhance the performance of heuristic control in IUDS.

6. Recommendations

The objective of this dissertation was completed, where volume-based heuristic predictive control was assessed, and the main research question and sub questions were answered. The results demonstrate that implementing RB-RTC with binary real radar rainfall forecasts in urban drainage systems can improve total CSO volume reduction by providing space in the sewer system beforehand and operating the WWTP at maximum capacity. This RTC strategy can potentially be enhanced by the adjustment of rules and set values. Additionally, the reliability of this strategy could be improved through longer simulation time periods using a larger amount of observed and forecast radar rainfall data.

The novelty of this strategy is the implementation of binary real rainfall forecast. Combining this forecast data with heuristic control could be a significant advance to develop a more efficient heuristic strategy for urban drainage systems. Based on rainfall characteristics, the selection process of a threshold, above which a storm event is forecasted over a particular horizon, is not properly delineated. In this study, different thresholds of the total rainfall depth were selected and tested to assess the response of the system, but it is still difficult to determine the optimum threshold to be used and how many thresholds should be considered. Not only the selection process of these thresholds should be further investigated, but also which rainfall characteristics are more suitable to identify a storm event and if one characteristic can be sufficient or multiple are needed. This could potentially improve the accuracy of the binary real forecast data.

Having assessed the implementation of binary real rainfall forecast on heuristic control, it would be interesting to use this data on optimization-based control (e.g., model predictive control) and to determine if this approach can also improve its performance. The next step would be to compare the heuristic control with optimization-based control, by implementing binary real forecast in both strategies, for a particular case study, and assessing performance indicators (e.g., CSO volume reduction) in the system.

Reducing CSO volume can help minimize the pollutant load increase in the receiving waters, but the quality of these discharges and how it is affecting the water bodies is not assessed. For this, the implementation of pollution and impact-based heuristic predictive control should also be explored, to mitigate the pollutant loads discharged in the receiving waters and prevent possible environmental and public health impacts. Since each IUDS can perform differently based on the objectives, the process of selecting RTC strategies also needs to be considered. A methodology or tool that accounts the benefits of implementing each of these heuristic predictive control strategies should be assessed, to determine the suitability of an RTC strategy for a particular case study.

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