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Research papers

Real-time control of combined sewer systems: Risks associated with uncertainties

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ABSTRACT

Model Predictive Control (MPC) of combined sewer systems can reduce environmental degradation caused by uncontrolled overflows. However, practical uncertainties are often neglected when assessing the potential of MPC strategies. This paper aims to understand the risks associated with using a non-perfect internal MPC-model, real precipitation forecast, and realistic dynamic system capacity fluctuations. An MPC with the objective to reduce the total combined sewer overflow (CSO) volume was implemented in the case study of Eindhoven in the Netherlands where highly sensitive waterways receive the sewer overflows. Two types of risks were identified: relative system performance loss and operative deterioration. The former entails a practical decrease in efficacy of controlling CSO spills compared to the theoretical situation, whereas the latter describes the aggravation of environmental pollution compared to a static form of system operation. The results obtained demonstrate that precipitation forecast uncertainty is associated with a small relative system performance loss. Opposite to this, significant performance loss was observed as a consequence of uncertainties in the internal MPC model and the actual sewer system capacity available. The latter caused additional combined sewer overflows compared to a statically optimised control for smaller precipitation events.

1. Introduction

Combined Sewer Overflow (CSO) structures are an important part of combined sewer systems (CSSs), designed to alleviate urban flooding by discharging urban runoff and wastewater into receiving water bodies when the CSS becomes overloaded. This release of untreated wastewater into the natural environment can result in ecological degradation of urban waters (Suárez and Puertas, 2005; Owolabi, Mohandes and Zayed, 2022), necessitating methods to mitigate or reduce CSO events. Real-Time Control (RTC), the optimisation of operations of actuators using real-time information about the system (Schütze et al. 2004), has been described as a potential cost-effective method to reduce CSO events by activating the static (e.g. in-sewer storage) and dynamic (WWTP inlet or pumping station) capacity of the CSS optimally (Dirckx et al. 2011).

RTC strategies can either be based on heuristic or optimisation-based algorithms (García et al. 2015). Optimisation-based algorithms commonly use models to predict the optimal settings for a system over a receding horizon in the form of Model Predictive Control (MPC) and show greater theoretical potential to optimise the CSS operation with regard to the set objective compared to heuristic algorithms (Lund et al. 2018). In MPC strategies real-time measurements of the system are used as initial conditions for an internal MPC model, precipitation forecasts as a forcing variable and pumping capacities as model parameters. The objective of the RTC can take many forms, but typically aims to minimise environmental impact directly (impact-based RTC), reduce the pollution loads from the CSS (pollution-based RTC) or the volume of CSO discharge (volume-based RTC).

To assert the performance of an MPC strategy prior to implementation, modelling studies are used (van Daal et al. 2017). This introduces a variety of sources of uncertainty which can impact the expected MPC performance. Uncertainties related to model parameters and precipitation forecast on model outputs have been studied (e.g. Achleitner et al. 2009; Deletic et al. 2012) but the influence of these model uncertainties on the performance potential of RTC strategies have not explicitly been considered (Lund et al 2020). Normally, the internal MPC model is often used as the model representing the system, thus negating any uncertainties that might occur (e.g. Sadler et al 2019; Sun et al 2020a). Considering precipitation forecast, several methods to account for

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precipitation uncertainty in an RTC setting have been proposed (Courdent et al. 2015; Svensen et al. 2021). Additionally, it has been argued that the precipitation uncertainty will not influence the final MPC performance significantly due to the re-updating of the initial conditions at every optimisation interval (Fiorelli et al. 2013).

Similar results were shown in other research, though the performance decreases (difference between the theoretical and uncertain data use), as shown in Table 1, vary widely, from almost negligible to almost half of the gained performance. From these publications, which use both MPC and Deep Reinforcement Learning (DRL), no clear trends in the performance loss could be established. Despite the many uncertainties potentially influencing the efficacy of RTC procedures highlighted, the main source of uncertainty assessed remains rainfall forecast/nowcast (Table 1, also see Lund et al 2018). Assessing the influence of this source of uncertainty seems to depend on how the uncertainty is modelled, as the use of real cases and large biases seems to exacerbate performance loss. Research on multiple (simultaneously modelled) sources of uncertainty, however, is limited to synthetically added noise to input data (thereby arguing the various uncertainties are compiled into a single uncertainty). Additionally, the use of real data to accurately represent the dynamics of uncertainty in a UDS context, remains limited. Although both methods have merit in the development of new, more robust control measures (e.g. Svensen et al 2021), it does not further the understanding of the relation between uncertainties and RTC efficacy nor enable further, targeted research.

Furthermore, during the operation of a CSS, changes to the system's dynamic capacity can occur as a result of pump failure, emergency or scheduled maintenance at the WWTP or pumping stations and other unforeseen events such as (partial) blockages. Failure events related to actuators show the highest level of risk within urban drainage systems (Miszta-Kruk, 2016). These temporary changes to the system capacity occur frequently in CSS and can exacerbate CSO volumes significantly in practice (Korving et al., 2006) for uncontrolled systems. As RTC strategies are designed to fully utilise the redundancy of the CSS capacity, the effects of these system capacity uncertainties on the system functioning is an important interaction to understand. RTC algorithms able to maintain functioning during failure operations, so called *fault-tolerant control*, either focus on failures in the information streams (Garofalo et al. 2017), or theoretical, local actuator failures (Ocampo-Martinez and Puig, 2009) and return to the 'pre-RTC' state when failures are detected (Pleau et al., 2004). The cumulative effect of the aforementioned uncertainties and failure mechanisms on the efficacy of an RTC strategy has not been studied before and was identified as a key gap in the RTC literature (van der Werf, Kapelan and Langeveld, 2022).

Table 1
Overview of the current literature assessing the functioning of various real-time optimisation procedures under uncertainty. Two types of control procedures have been reported on: Deep Reinforcement Learning (DRL) and Model Predictive Control (MPC).

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

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

Furthermore, the uncertain nature of the practical efficacy of RTC to improve storm water system performance remains one of the main concerns from practitioners (Naughton et al. 2021) and it can be assumed that these concerns apply to combined sewer system RTC as well. This results in limited practical applications of MPC (Lund et al. 2018). Research assessing the risks of practical operational uncertainties on MPC efficacy is needed to ensure more widespread implementation of the technology. The key novelty of this work will be to assess the relative importance of various sources of uncertainty (model induced, rainfall and system capacity uncertainties) using real operational and forecast data. This paper aims to develop and a methodology which systematically assesses the influence of different sources of uncertainty on the performance of model predictive control procedures and to quantify the influence of these sources of uncertainty on the MPC performance.

2. Methodology

The developed methodology aims to assess the risks of different uncertainties on the performance potential of an MPC scheme. These are computed based following a standardised methodology using the model-based performance of the RTC strategy under different scenarios with varying levels of uncertainty considered. First, an MPC architecture based on an optimisation model is set up and the sources of uncertainty within the architecture are determined (Section 2.1). Then, based on the identified sources of uncertainty, scenarios are defined (Section 2.2) and these scenarios are evaluated using a the risk-based assessment methodology (Section 2.3). If risks are identified, the underlying mechanisms are investigated. To illustrate the application of the methodology and to assess their influence on the relevant risks a case study and the control procedure used are presented in Section 3.

2.1. Model predictive control architecture

A centralised MPC architecture is developed using a full-hydrodynamic model to represent the physical combined sewer system. A conceptual model based on the full-hydrodynamic model has to be created for optimisation purposes (see Section 3 for details on the case study) hereafter denoted as the internal MPC model following the definition by Lund et al, (2018). The centralised MPC architecture follows the procedure outlined in Fig. 1. The full-hydrodynamic model is used to assess if there is a need for optimisation run: optimisation will only be done during conditions or predicted conditions within the forecast horizon that fall within the optimisation objective. Several sources of uncertainty exist in real MPC affecting the final optimal actuator settings (Fig. 1, data and processes indicated with dashed lines represent various sources of uncertainties considered in this work).

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

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

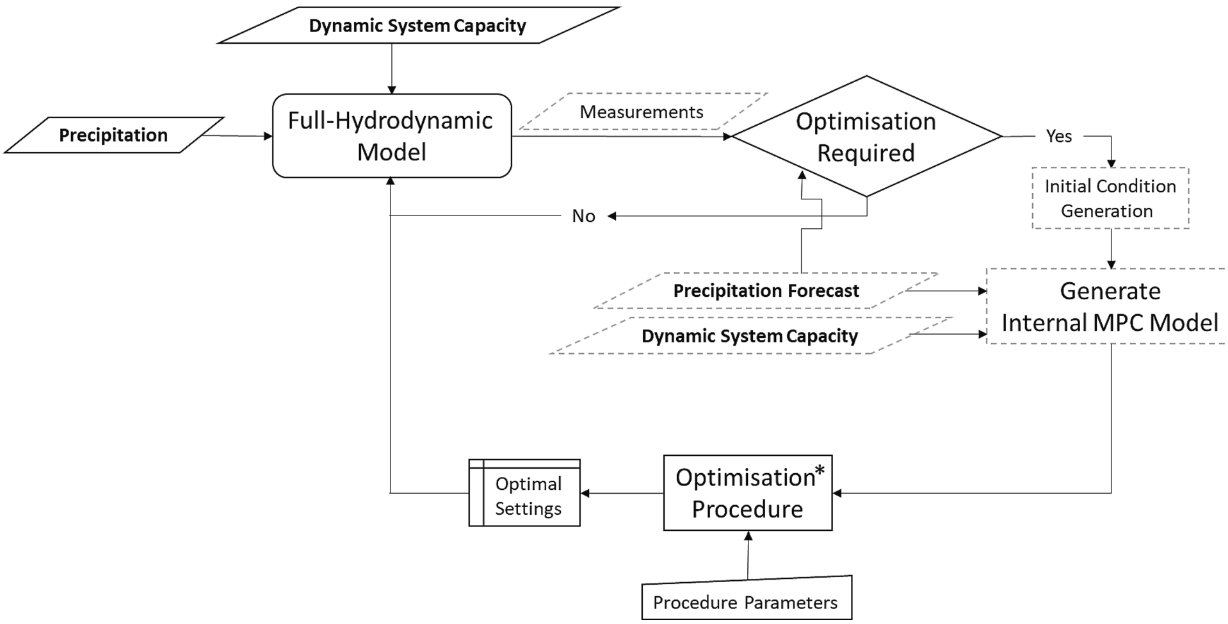

Fig. 1. MPC Scheme followed for every time step. Dashed lines indicate uncertain processes within the MPC scheme. * Optimisation procedure follows the method set out by Sadler et al. (2019).

forecasts (Löwe et al. 2016).

2.2. Uncertainty scenarios

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

The influence of the aforementioned sources of uncertainty can be determined stochastically and deterministically. Following a stochastic framework, random or semi-random errors can be introduced to the variables in order to generate the uncertain scenarios. However, the number of samples which can be used is limited given the real-time optimisation needs for MPC, making a stochastic framework impractical. A deterministic approach to uncertainty assessment involves defining a 'perfect information' and 'uncertain/real' case per variable, based on real data. The perfect information scenario refers to the scenario where the information parsed to the internal MPC model is entirely the same as the state of the UDS (or full-hydrodynamic model of the UDS), where the uncertain/real scenario refers to the scenario which would be the case for the implementation of MPC in a real system, using the real data. A deterministic approach was used in this research as it better represents the real uncertainties that occur within an MPC framework and it can give meaningful results without the computational burden of a stochastic approach. Details for both the cases per previously identified variable (Fig. 1) can be found in Table 2.

Three of the aforementioned variables require operational data: (1) Initial conditions requires operational understanding of the sensor output, (2) dynamic boundary condition uses observations of the functioning of the dynamics boundary condition (monitored pumping station capacity or WWTP capacity) and (3) the actuator functioning requires the reconstruction of previous set points and the comparison with the resultant set point for each actuator. There could be overlap between the latter two, if the pumping stations or WWTP are part of the control strategy. The other two (simplified model and precipitation forecast) both rely on model outputs only, and therefore do require the operation the CSS for data generation.

Table 2
Overview of the relevant uncertainties potentially impacting the performance of the MPC system.

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

The influence of the three sources of uncertainty for the internal MPC model mentioned in Section 2.1 were investigated in this paper: (1) simplification of the internal MPC-model, (2) precipitation forecast and (3) the dynamic boundary condition. These three were selected as data was available for the uncertain/real, as the other two require implementation of the studied control algorithm for data, which has not been implemented yet. Based on these three sources of uncertainty, five scenarios were defined, combining different sources of uncertainty with the internal MPC procedure (Table 3).

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

2.3. Risk and performance assessment

To quantify the risks associated with implemented RTC we define two risks: (1) the risk of relative system performance loss and (2) the risk

Table 3
Overview of used scenario pertaining to the information parsed to the internal MPC model.

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

of operative deterioration. The risk of relative performance loss quantifies the difference between the theoretical and real MPC performance based aforementioned uncertainties in the RTC design process (represented here using the five scenarios shown in Table 3) on observation data. The risk of operative deterioration is defined as the risk of operation of the sewer system using RTC that is worse than the static optimal operation (defined as having a single set-point for each actuator in the CSS).

To gain an objective insight in the functioning of an RTC system, an absolute Realised Potential Indicator (aRPI) was previously introduced (van der Werf, Kapelan and Langeveld 2021).The aRPI is calculated as the ratio between on the one side the difference between the RTC functioning and the statically optimised settings and on the other the difference between the maximum potential and the statically optimised settings following:

$$aRPI = \frac{J_{so,n} - J_{RTC,n}}{J_{so,n} - J_{MTP_a,n}} \tag{1}$$

where $J_{so,n}$ is the performance using static optimised control for event n, $J_{RTC,n}$ is the performance of the RTC strategy and $J_{aMTP,n}$ is the maximum potential performance calculated using an adjusted version of the central basin approach (Einfalt and Stölting, 2002). The aRPI ranges in theory from -∞ to 1, where a value close to 1 indicates a control strategy close to its maximum achievable potential, 0 indicates the same result as the static optimal setting and any negative value between.

First, the total aRPI and aRPIs per event are calculated for scenario 1 (i.e. the baseline scenario). These form the theoretically achievable potential of the MPC strategy. Then the total aRPI and aRPI per event are calculated for the other three remaining scenarios outlined in Table 3. The difference of the total aRPI for a given scenario and the total aRPI for the baseline scenario (i.e. scenario 1) is used as the final indicator of the risk of relative performance loss. The corresponding distributions of the aRPI are also assessed to see if there is a statistically significant difference between the scenarios, using the Kolmogorov-Smirnov test (KS-test). If there is a significant different between the scenarios, the dynamics in the system causing the difference are further investigated. If this isn't the case, the source or set of sources of uncertainty are deemed to not have a significant effect on the performance of the MPC procedure. Additionally, a relation of the risk of relative performance loss per event to precipitation and system capacity characteristics is then assessed by analysing the total rainfall depth, maximum rainfall intensity and median system capacity during wet weather flow operation.

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

3. Case study

3.1. Catchment details

The methodology described in previous section is demonstrated on the case study of Eindhoven, the Netherlands. The natural water bodies in this catchment experience nutrient overloading and oxygen depletion from both urban runoff (Moreno-Rodenas et al. 2019), agricultural pollution (Pieterse, Bleuten and Jørgensen, 2003) and WWTP effluent (Langeveld et al. 2013). This catchment has been studied before in the context of RTC of the full urban drainage system (Langeveld et al. 2013; van Daal-Rombouts et al. 2017). An extensive monitoring network with high quality data was implemented previously for both the river and sewer networks (Schilperoort, 2011). WWTP Eindhoven has three inlets serving 29 urban drainage networks with a total capacity of 750,000p.e. Of these, 23 drainage systems drain through Riool-Zuid (Southern Sewer), a large transport sewer system stretching nearly 30 km with pipe diameters ranging from 0.35 m to 2.25 m from the most upstream to the most downstream section.

Pumping station (PS) Aalst is located midway across this transport line. This pumping station has a design capacity of 12,000 m^3/h, however, the actual capacity used is limited to 10,000 m^3/h. Even this reduced capacity is not always used as evident from the flow measurements recorded downstream of this pumping station (see Fig. 2).

The section upstream of the PS Aalst is modelled and used in this study (Fig. 3). This section spans roughly 18 km from the northernmost to the southernmost nodes and 12 km from east to west. The full-hydrodynamic model consists of 10,509 nodes, 11,462 conduits and a total of 147 outlets (both CSOs and storm water outlets). Both the full-hydrodynamic and the internal MPC-model were developed in EPA SWMM 5.1.015 (Rossman, 2010) and ran through the Python interface PySWMM (McDonnell et al. 2020). Both models have been previously developed and calibrated (van der Werf, Kapelan and Langeveld, 2021). The internal MPC model was designed as a set of storage units representing the municipalities discharging into the transport sewer and was calibrated on the full-hydrodynamic model. It was deemed to have an acceptable performance as the mean NSE varied between 0.57 and 0.78. Flow rates through the system can be controlled by two large control stations in the transport line, CS De Meeren (the downstream most control station) and CS Valkenswaard (the upstream most control station), splitting the system into three sections. The flow rates through these control stations are the decision variables given to the centralised MPC procedure.

3.2. Control procedure

A volume-based RTC strategy was selected to minimise additional uncertainties inherent in models required for pollution- and impact-based RTC. Volume-based RTC remains a popular objective in the scientific literature and practice due to alignment with monitoring and regulations (Meng, Fu and Butler, 2020). To optimise the actuators at every time step following the used architecture (Section 2.1) a general objective function was formulated. The objective function used in this control procedure is based on the following three functions: (1) flooding minimisation, (2) CSO volume minimisation and (3) equal filling degree (Eq. (2), (3) and (4) respectively) following previously defined optimisation functions (Gelormino and Ricker, 1994; Pleau et al. 1996; Fiorelli et al. 2013). The objective functions are defined as follows:

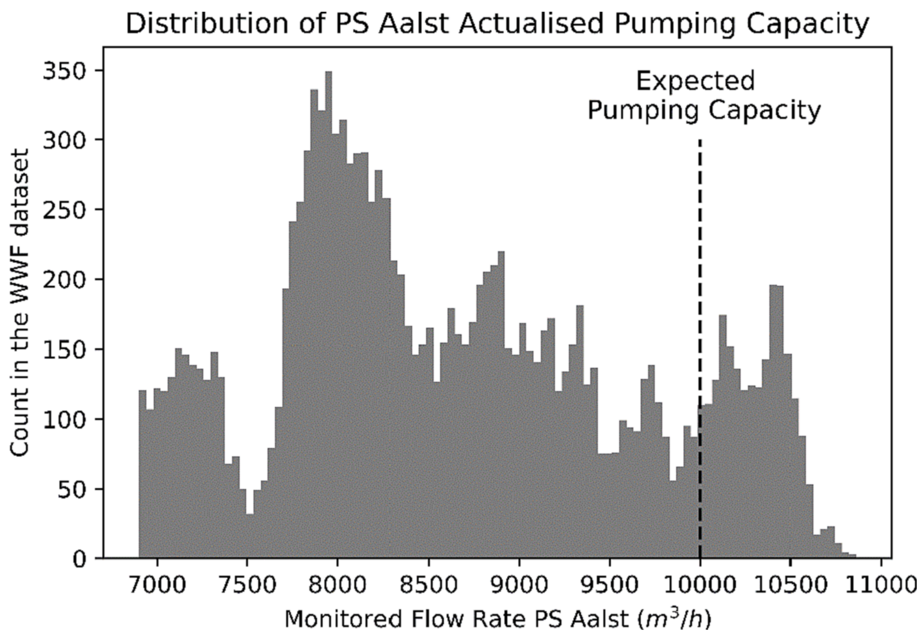

Fig. 2. Analysis of pumping performance of PS Aalst (bin size = 50 m3/h) during WWF.

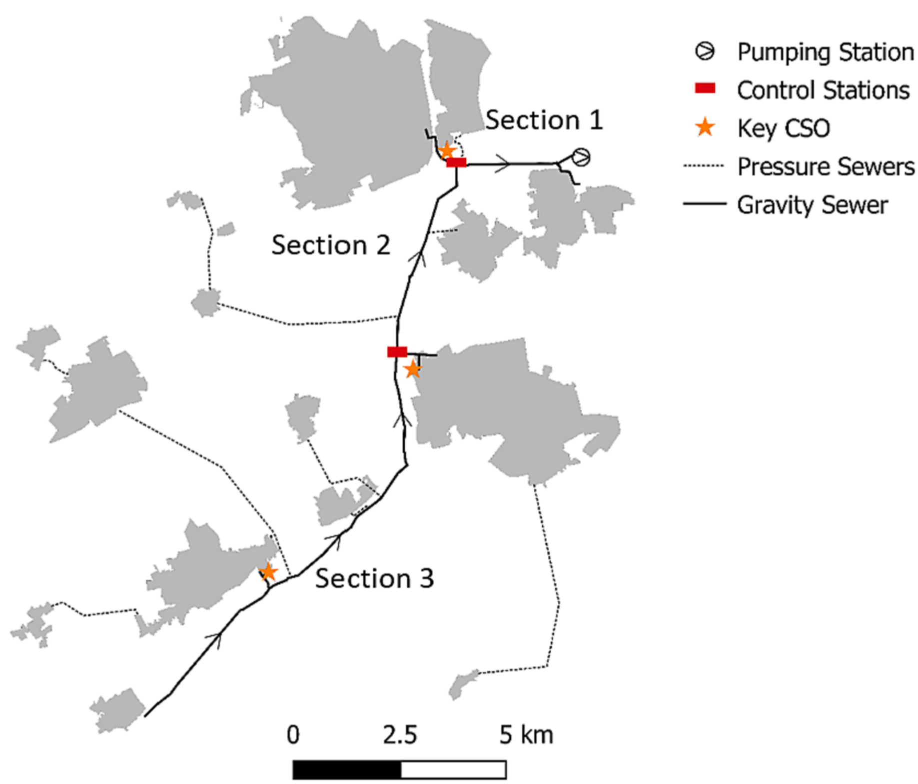

Fig. 3. Map of the investigated catchment.

$$J_{flooding}(T) = \Delta t \sum_{i=1}^{n_{nodes}} q^{i}_{flood} \quad (2)$$

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

$$J_{cso}(T) = \Delta t \sum_{i=1}^{n_{cso}} q^{i}_{cso} \quad (3)$$

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

$$J_{fillingdegree}(T) = \sqrt{\frac{\sum_{i=1}^{n_{sections}} (fd_i - \mu)}{n_{sections}}} \quad (4)$$

where $n_{sections}$ is the number of controlled sections, fd_i is the ith filling degree in the system, μ is the mean filling degree over all the section.

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

$$\min(a_1 * \boldsymbol{J}_{flooding} + a_2 * \boldsymbol{J}_{cso} + a_3 * \boldsymbol{J}_{fillingdegree}) \tag{5}$$

where a_1,a_2 and a_3 are weights used to discern the importance of each term, here set to 10000, 100 and 1 respectively. These weights were chosen to ensure clear prioritisation of flooding over CSO events, as within a GA framework these cannot be added as hard constraints. Note that third term in Eq. (5) was added to the optimisation objective to include equal filling of the system, even when CSOs are not predicted and thereby reducing risk of overflows occurring beyond the forecast horizon.

The optimisation function is subject to implicit constraints (mass and energy balance equations implemented in EPA SWMM5). To minimise undesired erratic actuator movement, the change in set point at every time step was explicitly constrained to a maximum change of 300 m^3/h per time step. This explicit constraint was added to avoid the need to add another objective to the objective function, as done in Sun et al. (2020a).

The above optimisation problem is solved using a conventional elitist Genetic Algorithm (Goldberg, 1989), as it is commonly applied in water resource management (Nicklow et al 2010) and urban drainage system modelling, with RTC in particular, for many years (Rauch and Harremoes, 1999). In this case study this is done every 5 min of simulation time, over a RTC forecasting horizon of 2 h. A GA population size of 20, mutation probability of 0.1 using a uniform mutation operation, crossover probability of 0.5 for uniform crossover operation, a parent portion of 0.25 and a rank-based selection operator were used. These parameters were iteratively chosen to ensure good search performance. The MPC scheme was run locally on a desktop with a four core Intel i5-6500 CPU @ 3.20 GHz cpu.

A local control procedure following a single-input-single-output structure for the two actuators, based on water level as input and flow rate as output, was previously developed and found to significantly reduce CSO volumes (for details see van der Werf, Kapelan and Langeveld, 2021). The set points for control station De Meeren is set to 5000 m^3/h and control station Valkenswaard is set to 2500 m^3/h and form the optimal static control for the system. These restrictions are reached by means of a moveable gate controlled by a local PID controller. This moveable gate is activated when wet weather flow (using a simple threshold for the observed downstream head) is detected inside the system and only opened when the system has gone back to dry weather flow.

For the catchment studied here, flooding issues do not occur frequently due to a CSO capacity of around 20 mm/hr. The inclusion of the flooding term in the objective function (Eq. (1)) therefore did not affect the actuator settings for the used catchment, but was included to follow a more generalised approach to MPC to facilitate and formalise result comparisons.

3.3. Precipitation

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

$$I = 10^{\frac{Z-109}{32}} * \Delta t^{-1} \tag{6}$$

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

The historical prediction data set spans the years 2014 and 2015. Precipitation events within these two years were selected. Usable events were defined as precipitation events resulting in wet weather flow throughout at least 2 sections of Riool-Zuid, with data available for pumping station Aalst. The latter requirement was only met for the 2015 data set. A total of 17 precipitation events from 2015 were used in the final analysis for Scenarios 2 till 5. This includes 'hybrid-events', i.e. events with various rainfall peaks considered as one event. The maximum intensities for the events ranged from 2.17 to 30.58 mm/hr (mean of 10.74 mm/hr) and depths ranging 6.2–43.5 mm (mean of 18.3 mm). Two rainfall events were used for assessing Scenario 1, with maximum intensities of 13. and 10.75 mm/hr, and total rainfall depths of 28.7 and 14.3 mm for events 1 and 2 respectively.

4. Results

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

4.1. Risk of relative performance loss

Scenario 1 can be seen as the highest possible achievable MPC performance for the used strategy and procedure, as it neglects all forms of uncertainty which might affect the performance (named here the theoretical functioning). Scenario 1 performed better for the events with a total aRPI of 0.79, compared to 0.50 for Scenario 2 (Table 4, Fig. 4), indicating both considerably improved the system functioning and relative proximity to the maximum achievable performance. Compared to the baseline, this represents a CSO reduction of 68.7 % and 44.4 % respectively. This equates to a 35 % relative loss, based on model uncertainty alone.

This difference was assessed by looking at the behaviour of the most downstream actuator in the system, which was noticeably different during the CSO events. During the phase of the event when the CSO occurred, in Scenario 1, the flow through Actuator 1 was restricted further compared to Scenario 2, reducing the CSO volume at the downstream locations (Fig. 4). This did cause a limited increase in the CSO rate at the upstream CSO, such that the total CSO volume was minimised. In Scenario 2, more flow was allowed through this control station, causing an overall increase in the CSO volume.

As Scenario 1 (the perfect baseline) could only be analysed for two events, Scenario 2 (the practical baseline) was used as the baseline for showing the maximum achievable potential of the used MPC scheme. The total CSO volume of Scenarios 2 till 5, following the MPC strategy set out in Section 3.2, were compared to the total CSO volume obtained using the static optimum settings as determined in previous work (van der Werf, Kapelan and Langeveld, 2021). Reductions in the total CSO volumes of the 17 analysed precipitation events were found for all four

Table 4
Difference between Scenario 1 and 2.

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

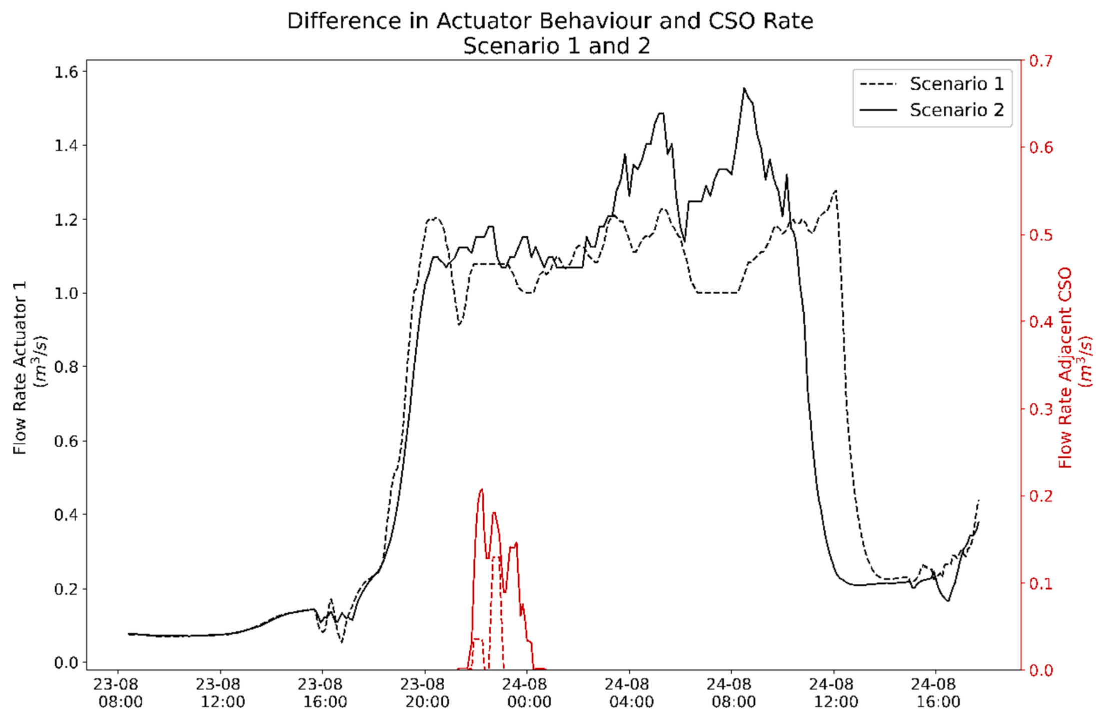

Fig. 4. Difference in actuator behaviour between Scenarios 1 and 2.

scenarios (Fig. 5a and b). The boxplots (whiskers indicating the 5–95 % CI) were constructed based on 12 events, as five of the used events did not cause overflows in the static optimum. These five events are further discussed in Section 4.2.

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

A relatively small relative performance risk was observed for Scenario 4 (using real radar forecast data in the optimisation-model), with an aRPI of 0.46 and CSO reduction of 20.3 % compared to the baseline, equating to a 14.4 % performance loss compared to Scenario 2 (Table 5). One CSO event was negated for Scenario 3, one less compared to Scenario 2. This suggest only a limited risk of relative performance loss when using radar forecasts. The frequent updating of the internal MPC model ensures that the importance of accurate forecasting is minimal. Recent advances in precipitation forecasting are therefore unlikely to yield higher practical performance from MPC systems. Longer horizons and application of precipitation forecasts to heuristic control have not been assessed in this work and might show different performance related risks.

A more pronounced relative performance risk was associated with assuming the full capacity of the downstream pumping station, with a relative reduction of 45.2 % and 47.3 % for Scenarios 3 and 5 respectively. Both scenarios exacerbated the frequency of the CSO events, with an increase in the number of events with CSO spills. This is further discussed in Section 4.2. The relatively large loss of performance corroborates findings by Sun et al. (2020b), which indicate a decrease in efficacy of the MPC scheme under variable WWTP capacity. They, however, consider their variable capacity as a process which can be modelled, whereas the pumping capacity decrease here is considered aleatoric in nature.

The uncertain precipitation forecast and pumping capacity together do not synergistically influence the performance of the MPC scheme in a significant manner based on these results. Indeed, the mean and median of the performance difference between Scenario 3 and 5 for these 14 events were 0.5 % and 0 % respectively. Assessing the statistical significance of the difference in performance, only the difference between Scenarios 2 and 3 and between Scenarios 2 and 4 were statistically significant (following a KS-test with $\rho < 0.05$), as indicated by the scatter plots in Fig. 6 (blue indicating significance, orange a lack thereof).

The relative increase in CSO volume for Scenarios 3 and 5 is associated with an increase in the spill volume of the most downstream CSO structure. As the optimisation-based RTC model assumes full dynamic capacity in the most downstream section of the sewer, it reduces less the flow rate through the control stations causing an accumulation of water in the downstream section leading to increased CSO volumes. An example of this behaviour is shown in Fig. 7, at the Control Station De Meeren, the most downstream of the two control stations. For the example in Fig. 7, Scenario 2 did increase the CSO volume at the upstream CSOs, however, that increase was less compared to the CSO volume it reduced at the downstream most CSO location.

A relation between the relative performance loss and precipitation characteristics was investigated too. Total rainfall depth was previously found to be the best indicator of CSO volume for uncontrolled catchments (Fu and Butler, 2012). No such relation could be found from the simulated events presented here (Fig. 8a–c). The size of the dataset hampers the ability to draw significant relations within the dataset, for which a larger dataset would be necessary. However, linear correlations between precipitation characteristics and performance loss are not expected, given that such linear relations are not present in RTC performance either Vezzaro (2022).

4.2. *Risk of operative deterioration*

The risk of operative deterioration was assessed for Scenarios 2–5. Although uncertainties associated with the optimisation-model (model parameter, structure and initial condition uncertainties) are present in all scenarios, no operative deterioration was found for Scenarios 2 and 4. However, for both Scenarios 3 and 5, for three and two precipitation

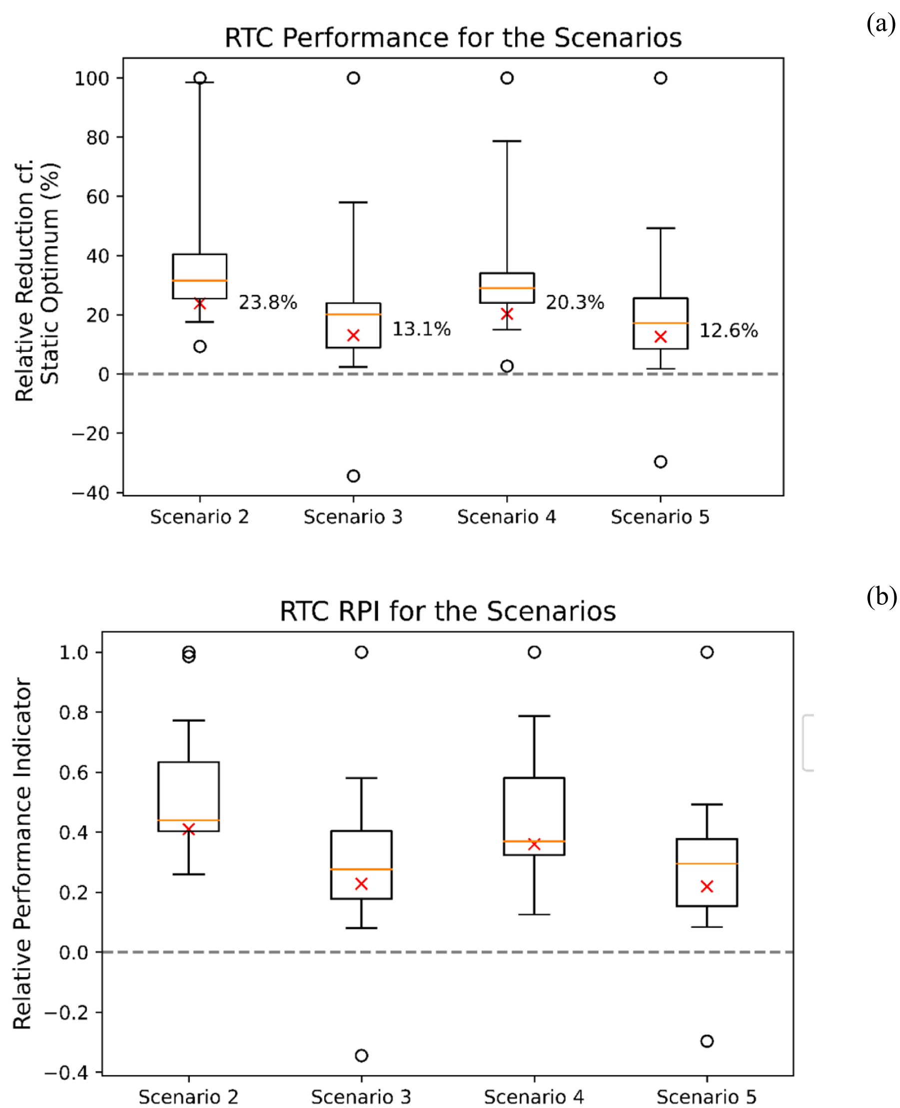

Fig. 5. (a) Relative Improvement of the RTC per scenario. (b) the RPI difference per scenario.

Table 5
Overview of the performance and performance loss per scenario.

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

events respectively, deterioration compared to the static optimal operation was observed, causing additional overflows and overflow volumes for these events.

The additional overflows occurred at the downstream section of the system, caused by the same mechanisms which caused the relative performance loss (Fig. 7). Although statistically significant statements cannot be made due to the relatively small sample size, the risk of operative deterioration seems to be the case for the smaller event with relatively large deviation in performance of the pumping station (Fig. 9). This is the type of precipitation event in which RTC typically has the highest potential (Vezzaro and Grum 2014; Kroll et al. 2018), which can mean potentially larger risks than reported here given the relatively small dataset within this range of events. Given that an MPC system aims to maximise the system's capacity, uncertainties in the downstream dynamic capacity can have a bigger influence on the system performance if this system is close to its maximum capacity, which is the case for smaller events.

5. Discussion

The uncertainty induced performance loss in this study fall within the range reported in literature (see Table 1). Although the relative performance loss of 14.4 % is more significant compared to the lowest bracket found (1.2–2.8 %), it is lower compared to the studies using real rainfall forecasts and the highest level of uncertainty (Jafari, Mousavi and Kim 2020; Zhang et al 2022). The latter, using a bias of ± 25 %, is comparable to the performance loss associated with the reduced pumping capacity (which is in the same range and is also considered a constant bias within the internal-MPC model). This is particularly interesting, as Zhang et al (2022) used a DRL optimisation procedure,

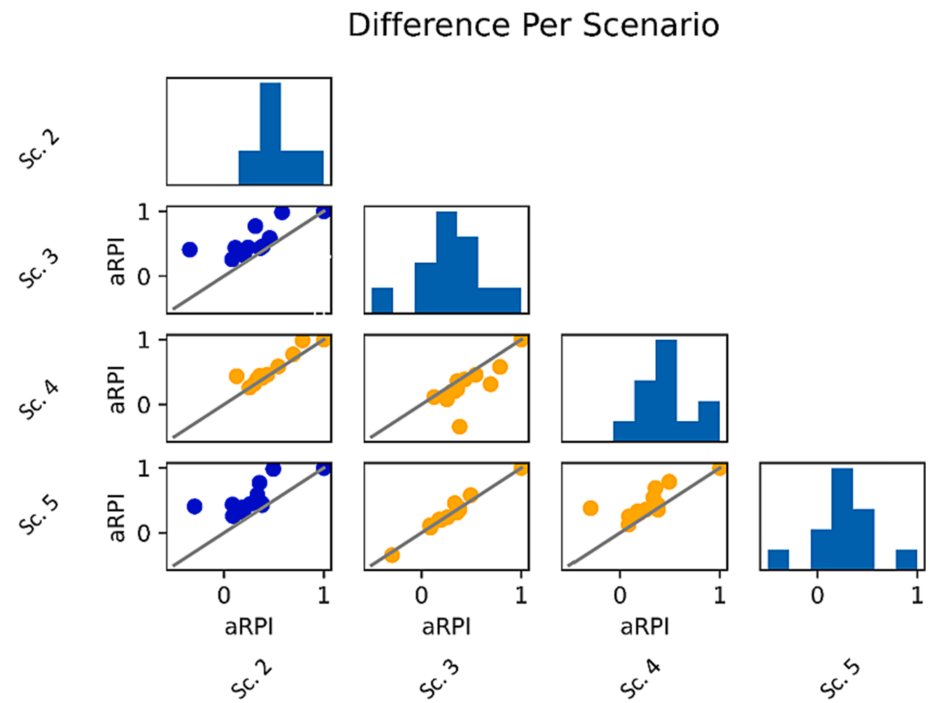

Fig. 6. Comparison between the Scenarios, blue indicating a statistically significant difference (KS-test, $\rho < 0.05$). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

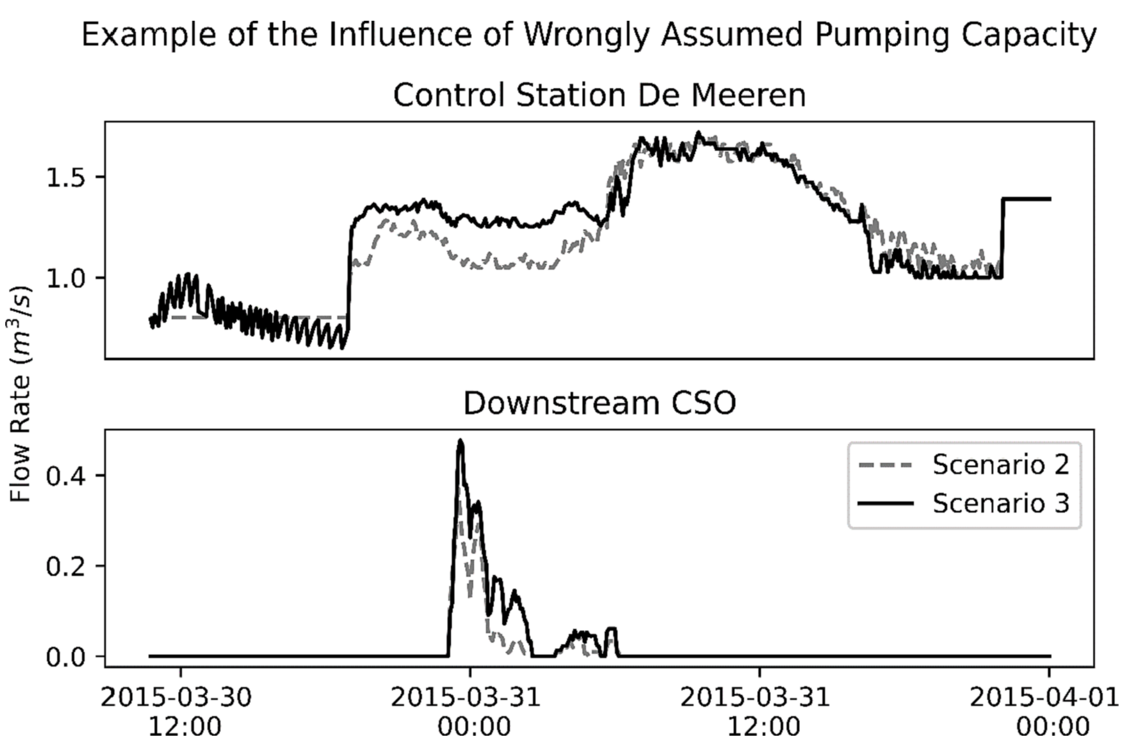

Fig. 7. Example on the different decision made by the optimiser.

indicating comparable results between different real-time optimisation procedures. It should be noted that the comparison with previous reported values remains difficult due to the case study specificity, relative RTC potential and rainfall events used. Values here are reported in the form of the aRPIs (van der Werf, Kapelan and Langeveld, 2021), with the aim to allow for better comparative assessment in the future.

The modelling results obtained here show the importance of considering the risks of relative performance loss within the design stage of the MPC strategy. Using this method allows the design of the MPC to be more robust against the perceived risks, and can give operators a more realistic insight in the implementable potential gains of MPC for their respective system. This, in turn, will aid in the decision-making process of investments for future rehabilitation projects of the UDS. Methods to deal with the various sources of uncertainties have been

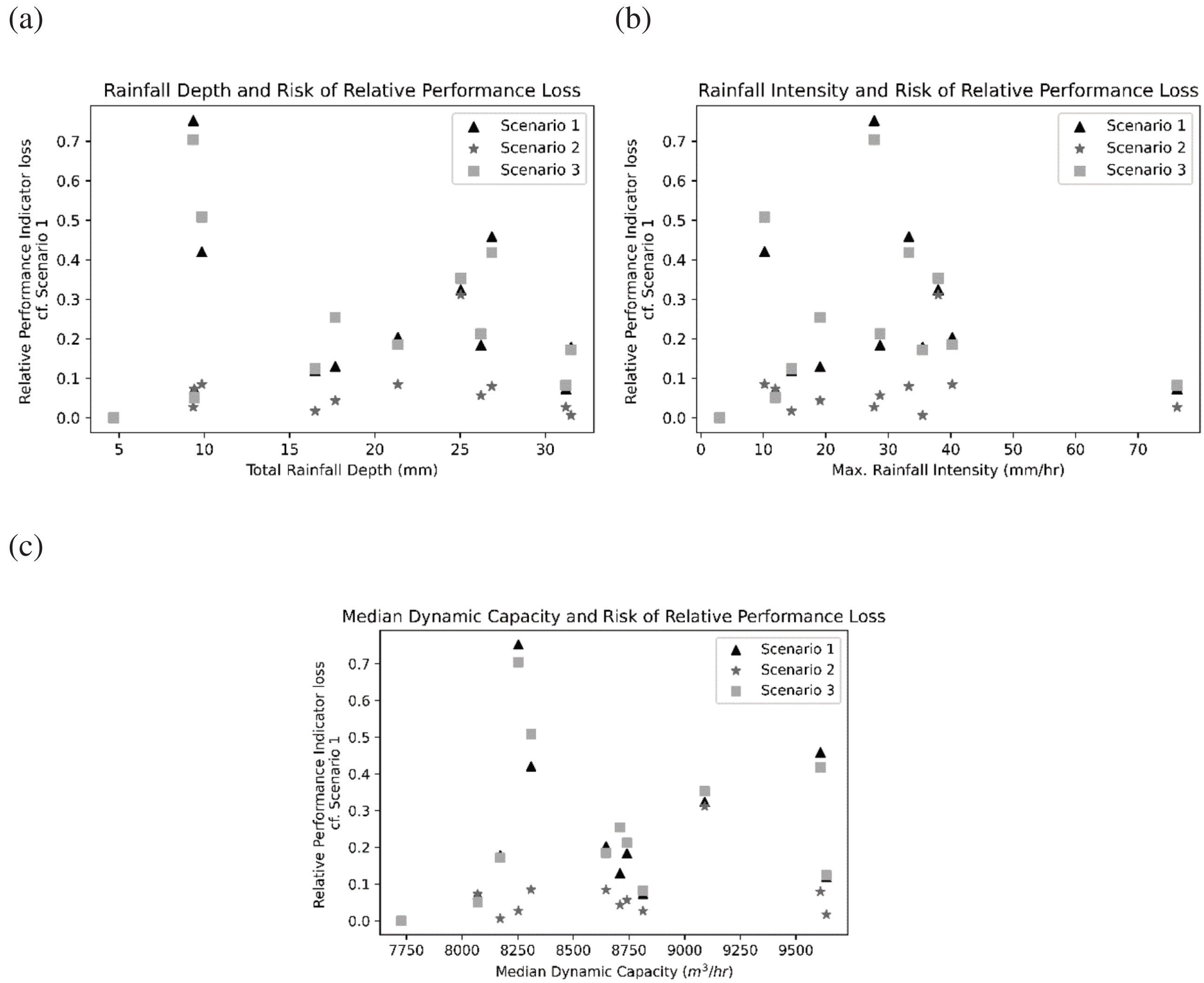

Fig. 8. (a) Relation between performance loss and total rainfall depth (b) relation between performance loss and maximum rainfall intensity and (c) relation performance loss and median dynamic capacity during wet weather flow.

proposed. Lund et al (2020) proposed a safety margin within their MPC structure of 5 %, allowing for random errors within the used model structure. Despite the relatively simple implementation of these safety margins, the robustness against incorrect model parameters was improved without large losses in the theoretical performance of the system.

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

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

6. Conclusion

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

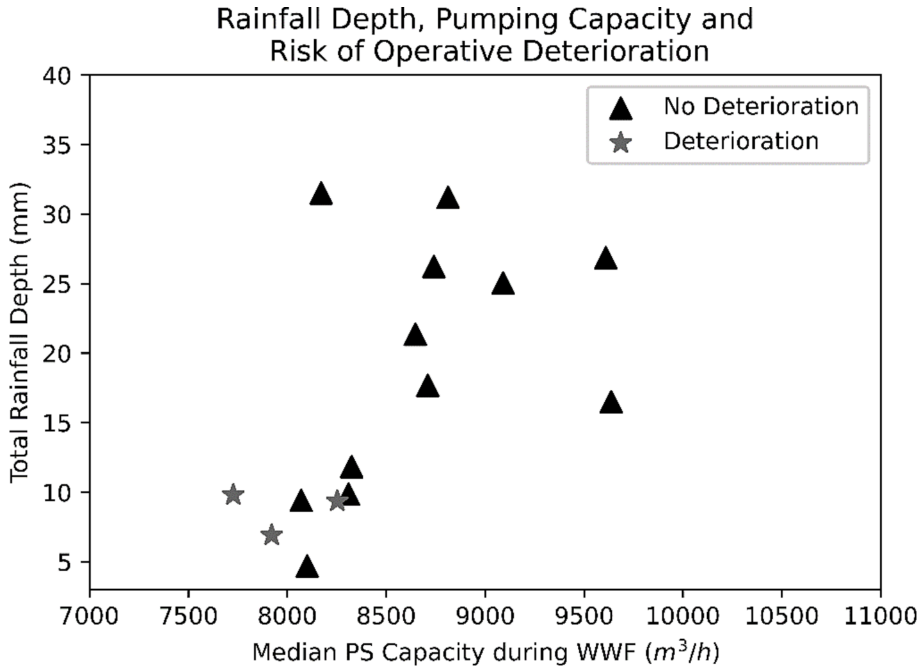

Fig. 9. Relation between the rainfall depth, median pumping capacity and operative deterioration for Scenario 2.

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

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

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

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

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

CRediT authorship contribution statement

J.A. van der Werf: Conceptualization, Methodology, Writing – original draft. **Z. Kapelan:** Supervision, Writing – review & editing. **J. Langeveld:** Supervision, Funding acquisition, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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