Integrated pollution-based real-time control of sanitation systems

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Highlights

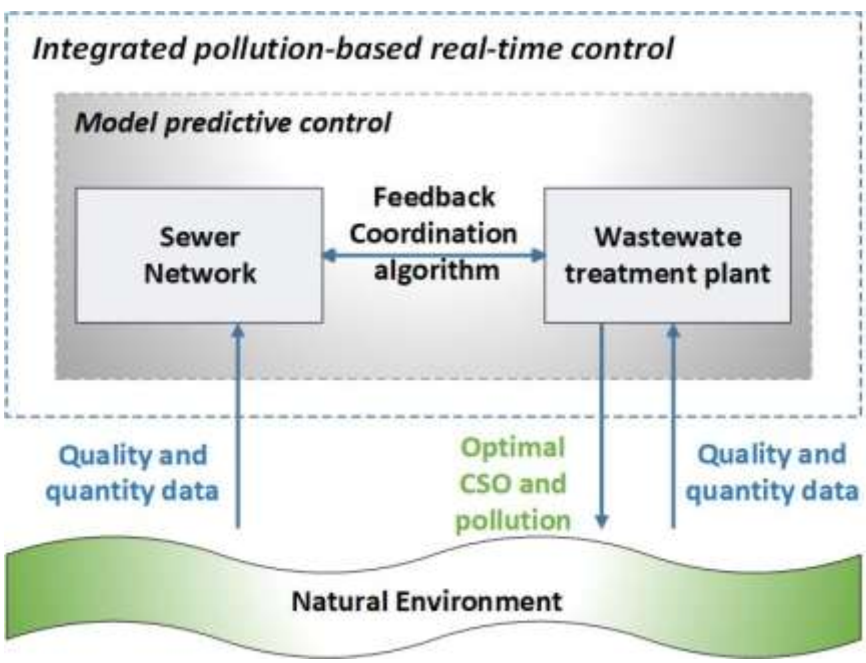
- Integrated pollution-based real-time control can reduce pollute of sanitation system.
- Model predictive control with quality dynamics generates optimal control strategy.
- Feedback coordination algorithm integrates subsystems during the control process.
- Closed-loop virtual-reality simulator accesses effectiveness of the control strategy.
- A real life pilot is used to demonstrate applicability of the proposed approaches.

ABSTRACT

An integrated pollution-based real-time control (RTC) approach is proposed for a sewer network (SN) integrated with wastewater treatment plants (WWTPs) in a sanitation system (SS) to mitigate the impacts of pollution from combined sewer overflows (CSOs) on ecosystems. To obtain the optimal solution for the SS while considering both quantity and quality dynamics for multiple objectives, model predictive control (MPC) is selected as the optimal control method. To integrate SN and WWTP management, a feedback coordination algorithm is developed. A closed-loop virtual-reality simulator is used to assess the results of the optimal management approach achieved by applying MPC. The Badalona SS (Spain) provides a pilot case study to assess the efficacy and applicability of the proposed approach. A comparison with local rule-based and volume-based control strategies currently in use indicates that the proposed integrated pollution-based RTC approach can reduce the pollutant loads released to the receiving environment.

Keywords: Integrated; Pollution-based; Real-time control; Model predictive control; Sanitation system

GRAPHICAL ABSTRACT



1. Introduction

Combined sewer systems, which carry wastewater and rainwater, are sometimes overloaded during heavy rain episodes and often cause combined sewer overflows (CSOs). These overflows contain a mixture of untreated domestic, commercial, and industrial wastewater, along with stormwater runoff, which can be a significant source of pollution (EPA, 2015) affecting aquatic ecosystems, human health, and the environment. Moreover, the rapid urbanization and global climate change have led to worse ecological conditions and have generated major environmental challenges worldwide (van Loosdrecht and Brdjanovic, 2014). To confront these challenges, official policies and regulations on water quality have been published worldwide, for instance the CSO Policy issued by Environmental Protection Agency in the United States (EPA, 1994; EPA, 2006; EPA, 2015), the Water Framework Directive (WFD, 2000/60/EC) (STW, 2013) established by European Union, and the "10-Point Water Plan" (Han, et al., 2016) released by China's Central Government. The sanitation system (SS), which generally comprises a sewer network (SN), one or more wastewater treatment plants (WWTPs) and a receiving body (e.g., rivers or coastal areas), is the main infrastructure to manage CSOs. Under this context, develop an advanced control approach for the SS in order to mitigate impact of CSO is in high requirement.

Traditionally, the construction of separated sewers and storage retention tanks and increasing the capacity of treatment facilities have been the primary ways of mitigating CSO pollution. Nevertheless, these approaches are limited by their high costs in terms of capital investment (e.g., an estimated $44.7 billion is needed for CSO abatement in the USA with a repayment time of up to 20 years) (EPA, 2015; Meng, et al., 2017). Also, selecting the location for CSO-reduction facilities is a major challenge given problems with land availability, community opposition, and competing land usage (EPA, 2015). Thus, solutions based solely on civil works are often not realistic in most urban areas.

Given the development of information and communications technology, real-time control (RTC) of SS has become a promising approach to reduce pollutions of CSOs without expensive investment in infrastructural expansion (Cembrano, et al., 2004; Meng, et al., 2017; Joseph-Duran, et al., 2014; Joseph-Duran, et al., 2015; Schütze, et al., 2004; Sun, et al., 2017a; Sun, et al., 2018a). By optimizing the use of storage for subsequent treatment as well as the proper management of WWTPs, especially during wet weather, efficient control strategies computed by RTC can maximize the efficiency of the SS infrastructure to prevent CSOs (EPA, 2015; Fu, et al., 2010). To date, RTC has been applied successfully to SSs, but most of those applications focused on only one subsystem. For example, in (Cembrano, et al., 2004; Joseph-Duran, et al., 2014; Joseph-Duran, et al., 2015; Puig, et al., 2009), RTC algorithms were applied to SNs, and it was assumed that the WWTPs had a constant capacity. In practice, WWTP capacity can vary significantly during rain events, and SN flow sent to a WWTP in excess of its actual capacity can cause CSOs. Thus, it is clear that to take advantage of the entire infrastructure, the management of SNs and WWTPs must be integrated.

Integrated RTC of SSs has been analyzed in the literature over the past few years using different approaches: a) volume-based RTC, which focuses on minimizing the amount of CSO discharged to the receiving waters; b) pollution-based RTC, which seeks to minimize the total amount of pollutants released to the environment; and c) emission-based RTC, which aims to directly maximize the quality of the receiving water (Joseph-Duran, et al., 2016; Vanrolleghem, et al., 2005). Among these approaches, emission-based RTC is superior in terms of environmental protection (Vanrolleghem, et al., 2005). However, emission-based RTC is difficult to implement because it requires real-time measurements and complex models that consider spatial and temporal changes in quality parameters inside receiving waters (Joseph-Duran, et al., 2016). Previous studies (Métadier and Bertrand-Krajewski, 2011; Meng, et al., 2017) have shown that pollution-based RTC provides a new and promising approach when several quality variables can be measured or estimated in real time.

Various methods have been proposed for generating optimal RTC control strategies, for instance the genetic algorithm (Fu, et al., 2008; García, et al., 2015), rule-based control (Schütze, et al., 2003) and model predictive control (MPC) (Cembrano, et al., 2004; Ocampo-Martínez, et al., 2013; Puig, et al., 2009). Genetic algorithm is a class of evolutionary methods which have been developed over the past few years for the RTC of SSs (Fu, et al., 2008; García, et al., 2015). Genetic algorithm can solve multi-objective problems with global optimal actions using probabilistic iteration mechanism. However, the high computation load and potential "premature" problem prevent its usage into large scale systems. Rule-based control is a widely used RTC strategy for SSs in practice (Schütze, et al., 2003; Schütze, et al., 2017; Sun, et al., 2020a; Sun, et al., 2020b) because of its simplicity of defining rules (in the format of "if-then-else") without modelling requirement (Elbys, et al., 2018; García, et al., 2015; Klepiszewski and Schmitt, 2002). Considering quality of the rule-based control is highly depended on experience of the person who defines the rules, and the optimal control solutions cannot be guaranteed.

Model predictive control is an optimization approach which uses a model of the system and forecasts of external variables to derive future optimal control strategies. Several previous studies have described the application of MPC in urban drainage control with significant reduction in CSO (Cembrano, et al., 2004; Joseph-Duran, et al., 2015; Ocampo-Martínez, et al., 2013; Puig, et al., 2009; Xu, et al., 2013). Optimal control strategies can be guaranteed from MPC regarding the fact that MPC considers not only current state but also future forecast states of the systems during the computation process. Besides, through developing control-oriented models using simple mathematical equations, MPC can be applied in large scale SS with limited computation efforts. Up to now, most of MPC applications in SS are focused on only one subsystem without considering the quality data either (Cembrano, et al., 2004; Joseph-Duran, et al., 2015; Ocampo-Martínez, et al., 2013; Puig, et al., 2009).

The main contributions of this work are: 1) Proposing an integrated pollution-based RTC approach for SSs, using MPC to minimize the pollution impact of CSOs. 2) The MPC state-space model and objective function were built considering both the quantity and quality dynamics of flows in the SSs and effluents. The approach uses the total suspended solids concentration (TSS) as a key quality parameter given that TSS is generally correlated with turbidity, which can be measured continuously online. Additionally, TSS can provide information on other relevant correlated quality parameters (Campisano, et al., 2013). The hydraulics and TSS dynamics in the SS were represented by simplified mathematical equations, which were used as constraints in the optimization procedure. 3) To integrate SN and WWTP subsystems during the optimization process, a feedback coordination algorithm was developed. 4) A real pilot study of the Badalona SS in Spain provided a case study. A closed-loop virtual reality (VR) simulator was used to evaluate optimal actions for the proposed control approach for the case study.

The rest of this paper is organized as follows. In Section 2, the simplified quantity and quality models are described briefly. Next, we present the MPC controller with both quantity and quality dynamics. We then explain a feedback coordination algorithm for SN and WWTP integration during the optimization process, as well as a closed-loop VR simulator to implement the control actions. In Section 3, the proposed approaches are applied and validated using the Badalona SS in a VR simulation environment, and we discuss the implementation of the integrated pollution-based

RTC approach. Finally, in Section 4, we discuss where some improvements could be made, as well as topics requiring future attention.

2. Methodology

In the SS, detention tank, gates and pumps, as well as the rainfall runoff are the main components, where the water volume and TSS mass in the detention tank used to behave as the state variable, the actuators (i.e. gates and pumps in SN and WWTP) are the control handle variables and the rainfall runoff is the disturbance in the control problem. The goal of the proposed methodology is to produce control strategies for the detention of water inside a SN that minimizes the polluting impact of CSOs during storm events while considering the most up-to-date information on WWTP capacity. To achieve these goals, an integrated pollution-based RTC approach has been developed through modules of Simplified models, MPC formulations, Feedback coordination algorithm and the Closed-loop VR simulator defined in Subsection 2.1, Subsection 2.2, Subsection 2.3 and Subsection 2.4.

2.1 Simplified models

The simplified model of an SS is used to predict dynamic changes in water and TSS in a control horizon. All of the conceptual SS modeling approaches try to represent complex physical phenomena in a simplified manner. However, there is no direct mathematical association between conceptual and physical-based models. In this section, the simplified model of hydraulics and TSS is described for sewers, detention tanks, and junction nodes. The TSS model for the detention tank, the mass balance model for the junction node, as well as the inlet TSS computation for WWTP are presented for the basic routing of TSS in SS (Sun, et al., 2017b; Sun, et al., 2018b).

1) Simplified TSS model for detention tank

The simplified model of TSS in a detention tank is based on a simple representation of the tank volume and the TSS mass evolution. First, the SS hydraulic tank model is presented as (Cembrano, et al., 2004)

$$\boldsymbol{vol}(k+1) = \boldsymbol{vol}(k) + \Delta t\left(\sum_{i=1}^{n_{in}} \mathrm{q}_{in}^{i}(k) - \sum_{i=1}^{n_{out}} \mathrm{q}_{out}^{i}(k)\right), \tag{1}$$

where $\boldsymbol{vol} \in \mathbb{R}^{n_t}$ represents the vector of water volume (m^3) stored in the tanks with their physical range in [0, $\boldsymbol{vol}^{max}$]; Δt is the sampling time (s), and k is the time step; $\boldsymbol{q}_{in} = (q_{in}^1, q_{in}^2, \cdots, q_{in}^{n_{in}}) \in \mathbb{R}^{n_{in}}$ is the vector of flows (m^3/s) going into the tank; $\boldsymbol{q}_{out} = (q_{out}^1, q_{out}^2, \cdots, q_{out}^{n_{out}}) \in \mathbb{R}^{n_{out}}$ is the vector of flows (m^3/s) going out of the tank; $n_t, n_{in},$ and n_{out} are the numbers of tanks, input flows, and output flows of the tanks, respectively.

According to Eq. (1), the water volume collection capacity of a detention tank is based on upstream and downstream differences in water flow. Similarly, the mass of suspended solids is collected in the detention tank based on the mass difference between inputs and outputs:

$$\boldsymbol{m}(k+1) = \boldsymbol{m}(k) + \Delta t\ (\sum_{i=1}^{n_{in}} q_{in}^{i}(k) tss_{in}^{i}(k) - \sum_{i=1}^{n_{out}} q_{out}^{i}(k) tss_{out}^{i}(k)), \tag{2}$$

where $\boldsymbol{m} \in \mathbb{R}^{n_t}$ is the total mass (kg) of the suspended solids in the detained water; $\boldsymbol{tss}_{in} = (tss_{in}^1, tss_{in}^2, \cdots, tss_{in}^{n_{in}}) \in \mathbb{R}^{n_{in}}$ and $\boldsymbol{tss}_{out} = (tss_{out}^1, tss_{out}^2, \cdots, tss_{out}^{n_{out}}) \in \mathbb{R}^{n_{out}}$ are the TSS concentrations (kg/m^3) for the water at the inlet and outlet of the tank, respectively.

Given that TSS models are used only to provide an understanding of the performance of the proposed control approach, the TSS dynamics in the detention tank can be simplified as the mixture behavior of the TSS mass, wherein mass sedimentation and erosion effects are not considered, the control interval is small (5 min), and new measurements are available at each control interval.

Assuming the detention tank has a constant TSS at different positions, the concentration vector of suspended solids in the detention tanks $\boldsymbol{tss} \in \mathbb{R}^{n_t}$, which is also the TSS at the outlets, can be computed as (valid for $\boldsymbol{vol} \neq 0$)

$$\boldsymbol{tss}\ (k+1) = \frac{\boldsymbol{m}(k+1)}{\boldsymbol{vol}\ (k+1)}. \tag{3}$$

2) Mass balance model for junction nodes

The junction node corresponds to the element where the TSS mass (and also flow) are split or merged according to the mass balance equation:

$$\sum_{i=1}^{n'_{out}} q_{out}^{i}\ (k) tss_{out}^{i}(k) = \sum_{j=1}^{n'_{in}} q_{in}^{j}\ (k) tss_{in}^{j}(k), \tag{4}$$

where q_{in}^{j} is the flow variable (m^3/s) through sewer j entering the junction; q_{out}^{i} is the flow variable (m^3/s) through sewer i leaving the junction; tss_{out}^{i} (kg/m^3) is the TSS concentration for outflow i; tss_{in}^{j} (kg/m^3) is the TSS concentration for input flow j; and n'_{out} and n'_{in} are numbers of the outflow and inflow branches, respectively, at this junction node.

3) Inlet TSS of WWTP

Processing at a WWTP usually consists of three steps: pre-, primary, and secondary treatment. During these treatments, physical, chemical, and biochemical reactions take place before discharging treated water to the receiving environment (Martínez, et al., 2016). Here, the detailed WWTP reactions were simulated using a VR simulator (GPS-X) (Sofia, 2014). At each time step, specific calculations derive a prediction of the WWTP capacity, $q_{wwtp}^{lim}(k)$.

2.2 Model predictive control formulations

The optimal control problem of MPC seeks to derive ahead of time the optimal control strategies for gates and pumps in the SS based on the simplified models defined in Subsection 2.1 and the performance function over a future horizon.

According to the basic formulation of MPC (Maciejowski, 2002), the optimal control problem for MPC in the SS can be described using a state-space discrete-time representation of the model:

$$\min_{\boldsymbol{u}(k)} \boldsymbol{J}(k) \tag{5a}$$

s.t.:

$$h\big(\boldsymbol{x}(k), \boldsymbol{u}(k), \boldsymbol{w}(k)\big) \geq 0, \tag{5b}$$

$$g\big(\boldsymbol{x}(k), \boldsymbol{u}(k), \boldsymbol{w}(k)\big) = 0\ , \tag{5c}$$

$$\boldsymbol{x}_{min} \leq \boldsymbol{x}(k) \leq \boldsymbol{x}_{max}\ , \tag{5d}$$

$$\boldsymbol{u}_{min} \leq \boldsymbol{u}(k) \leq \boldsymbol{u}_{max}\ , \tag{5e}$$

where $\boldsymbol{J}$ is the objective function, $\boldsymbol{x} \in \mathbb{R}^{n_t}$ is the system state vector, which represents the water volume $\boldsymbol{vol}$ and TSS mass $\boldsymbol{m}$ in all of the tanks; $\boldsymbol{u} \in \mathbb{R}^{n_g}$ is the vector of controlled flows through the gates and pumps in the SS with n_g numbers of control gates; $\boldsymbol{w} \in \mathbb{R}^{n_d}$ is the sequence of disturbances related to rain runoff and incoming TSS through runoff with n_d numbers of disturbances. The functions $h(\cdot)$ and $g(\cdot)$ include the general constraints of the MPC problem, $\boldsymbol{u}_{min}$, $\boldsymbol{u}_{max}$, $\boldsymbol{x}_{min}$, $\boldsymbol{x}_{max}$, which are the vectors of physical limits, and $k = t, \ldots, t + H$, where t is the current time step, and H is the prediction horizon.

The following performance functions were included in the multi-objective cost function:

1) CSO volume minimization

$$\boldsymbol{J}_{cso}(k) = \Delta t \sum_{i=1}^{n_{cso}} q_{cso}^{i}(k)^2 + q_{bypass}(k)^2, \tag{6}$$

where n_{cso} is the number of CSO-diverting points, q_{cso}^{i} is the flow of CSO i released to the receiving environment; variable $q_{bypass}(k)$ is the bypassed CSO from the WWTP when the incoming water exceeded the treatment capacity.

2) WWTP usage maximization

WWTP usage is maximized through minimizing the difference between q_w (the flow incoming to the WWTP) and q_{wwtp}^{lim} (the maximum flow that can be accepted by the WWTP). This objective is expressed as

$$\boldsymbol{J}_{wwtp}(k) = \left(q_w(k) - q_{wwtp}^{lim}(k)\right)^2. \tag{7}$$

3) Control smoothness

Smoothness of actuator control is achieved by minimizing variation in the control between two consecutive time steps to provide a smooth strategy for the control elements:

$$\boldsymbol{J}_{smoothness}(k) = \sum_{i=1}^{n_g} \left(u^i(k) - u^i(k-1)\right)^2, \tag{8}$$

where n_g is the number of control gates as defined previously, and u^i represents the flow set-point variable produced by controller i.

4) Pollution minimization

The pollutant loads from CSO to the environment is minimized. This quality objective function to minimize the overflowed mass of suspended solids is provided by

$$\boldsymbol{J}_{mass}(k) = \sum_{i=1}^{n_{cso}} tss_{cso}^{i}(k) q_{cso}^{i}(k) + tss_{bypass}(k) q_{bypass}(k), \tag{9}$$

where q_{cso}^{i} is the sequence of flows (m^3/s) at CSO point i; tss_{cso}^{i} is the sequence of TSS concentrations (kg/m^3) at CSO point i; q_{bypass} is the flow (m^3/s) at the WWTP inlet bypass; and tss_{bypass} is the TSS concentration (kg/m^3) at the WWTP inlet bypass.

After combining these goals, the objective function for the MPC of SS can be expressed as:

$$\boldsymbol{J}(k) = a_{cso}\boldsymbol{J}_{cso}(k) + a_{wwtp}\boldsymbol{J}_{wwtp}(k) + a_{smoothness}\boldsymbol{J}_{smoothness}(k) + a_{mass}\boldsymbol{J}_{mass}(k), \tag{10}$$

where a_{cso}, a_{wwtp}, $a_{smoothness}$, and a_{mass} are tuning weights that can be adjusted according to the desired prioritization established by the system operators. This objective function must be summed along the horizon from instant k to $k+H$.

2.3 Feedback coordination algorithm

In current local control implementations, the SN is generally controlled separately from the WWTP by considering a nominal hydraulic treatment capacity. However, to protect the biological treatment process of the WWTP from harmful conditions that may eventually cause a failure or a loss in efficiency, we consider dynamic treatment capacity that continuously takes into account the WWTP operating conditions so that the updated treatment capacity is integrated with the SN optimization using a feedback coordination algorithm (Sun, et al., 2015; Romero-Ben, et al., 2019).

The communication between SN and WWTP is coordinated in a feedback loop (Fig. 1). At every sampling time Δt iteration, the WWTP capacity calculator produces the predictive treatment capacity for the following predictive horizon H and updates the bound of the MPC model in the SN.

Using the WWTP capacity prediction, among other required data, the MPC produces an optimal gate/pump operation sequence which ensures that the SN sends permissible wastewater flows to the WWTP.

Here, the SN was simulated in InfoWorks (MWH, 2010), and the WWTP was simulated in GPS-X (Sofia, 2014). The calculator module was based on the state point analysis criterion (detailed in (Keinath, 1985)). The MPC-based integrated management strategy was implemented using the GAMS optimization library (Rosenthal, 2013) with a 30-min prediction horizon and a 5-min control interval.

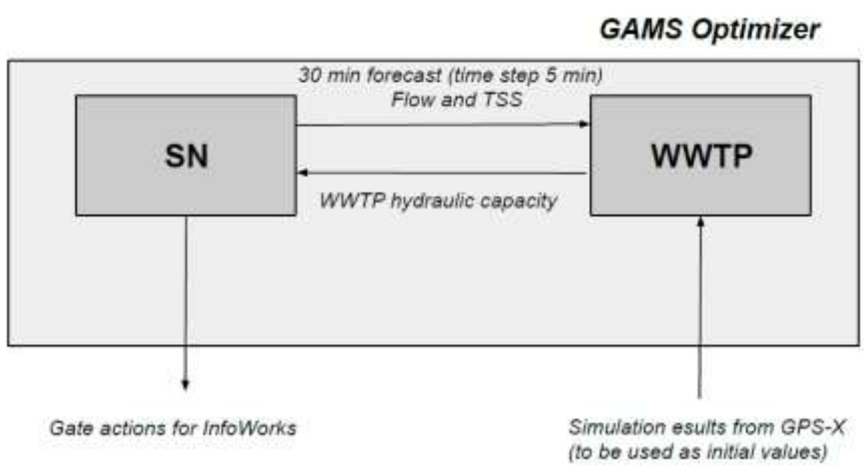


Fig. 1. Feedback coordination algorithm.

2.4 Closed-loop VR simulator

The results of the MPC control strategies were accessed and validated through a VR simulation framework based on software tools InfoWorks and GPS-X.

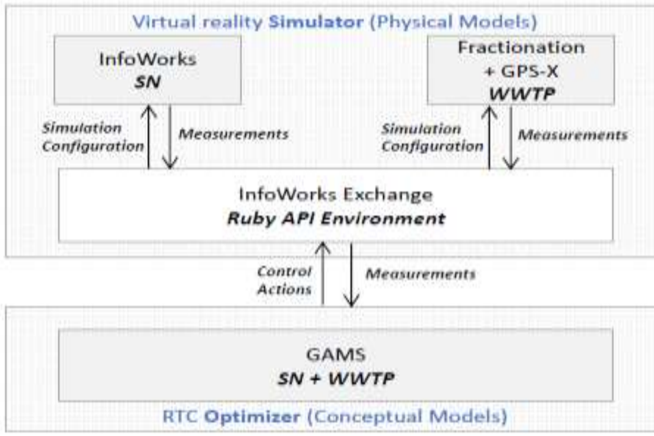


Fig. 2. Closed-loop simulation framework.

The simulation framework works in a closed loop with the MPC-based optimization where the simulators and controller exchange information involves the following at each time step: 1) Running the detailed simulators (InfoWorks and GPS-X) with a rain forecast to estimate the current state of the network and predict subsequent values of runoff and TSS at the different inlets in the sewer. 2) Using the WWTP capacity calculator to derive a prediction of WWTP capacity for the next horizon, in this case 30 min ahead. 3) Retrieving the current state, the input runoff flow, TSS predictions and the predicted WWTP capacity to execute the MPC and obtain optimal strategies for the next time horizon in GAMS. 4) Applying the set point for the first time step in the horizon to the SN actuators, moving forward one-time step, in this case 5 min, and starting again from action 1).

3. Case study

3.1. Case study

The case study in this paper is based on the Badalona SS, an area of approximately 20 km² in the east of Catalonia (Spain) with approximately 200 000 inhabitants and facing the Mediterranean Sea (Fig. 3).

Fig. 3. Map of Badalona location (in violet).

Badalona has a Mediterranean climate, with 50% of the rainfall occurring during two or three heavy rainfall events in the summer and autumn. During the most intense storm events, a portion of the stormwater cannot enter the WWTP, leading to CSOs on the beaches of Badalona with serious environmental, social, and economic consequences.

The case study includes a combined SN (blue line in Fig. 4) and a WWTP. The main detention infrastructure is the Estrella tank (blue cylindrical element labeled “DLES” in Fig. 4). The Besòs WWTP is located on the coast. The flow sent from the Badalona Municipality SN to the WWTP is constrained by the pumping station. Along the coast, there are several outfall points from which CSOs are released (in red in Fig. 4).

Fig. 4. Badalona sanitation system (SS).

3.2. Detailed model for simulation

The detailed model of the SN at the Badalona pilot (Fig. 5) was implemented in InfoWorks Integrated Catchment Modelling (InfoWorks ICM) (MWH, 2010) from the Innovyze Company. To simulate the Badalona pilot, the hydraulic models based on full one-dimensional Saint Venant equations and InfoWorks (Joseph-Duran, et al., 2014) were used. Furthermore, InfoWorks ICM offers the Ackers–White model, Velikanov model (Combes, 1982), and KUL model (Joseph-Duran, et al., 2014) for simulating the erosion, transport, and deposition of sediments as pollutants travel in suspension or attached to solid particles. We used the Velikanov model, and the TSS was used as the quality indicator.

Fig. 5. InfoWorks Badalona detailed model.

The detailed WWTP model was implemented in GPS-X (Sofia, 2014), which provides a modular multipurpose modeling environment and uses an advanced graphical user interface to facilitate dynamic modeling and simulation. The GPS-X simulation was built using the Advanced Continuous Simulation Language (Sofia, 2014), which has powerful integration capabilities and general simulator features. The GPS-X WWTP model layout is shown in Fig. 6 and includes the typical treatment processes of conventional WWTPs: gravity clarifiers as the primary treatment, a conventional suspended growth biological process as the secondary treatment, and a simplified sludge line with thickening and dewatering processes.

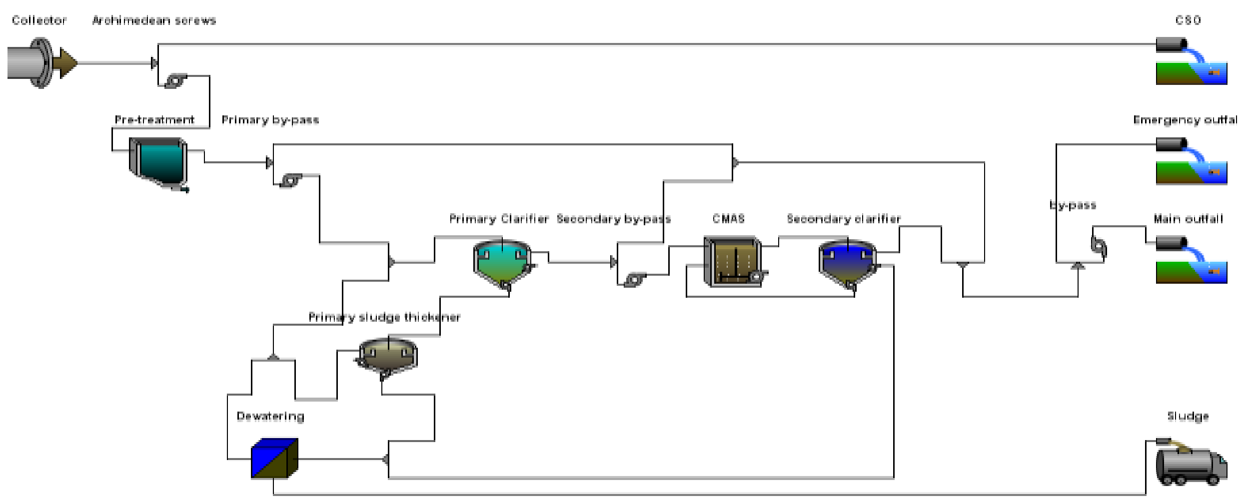


Fig. 6. Wastewater treatment plant (WWTP) layout of Badalona pilot in GPS-X.

3.3. Simplified network structure for optimization

For the computation of control strategies using MPC, a simplified model structure described below (Fig. 7) was used to represent the basic dynamics of the SN. Details of the simplified modeling approach and its calibration are provided in (Martínez, et al., 2019). The simplified network contained eight catchments (C1–C8) and Baux. The catchments were connected by 35 links. Also present a detention tank (T1); two gates, which controlled the flow of water into the tank; pumping stations to empty the tank; and four overflows (CSO1–CSO4) and the overflow of the TWWTP tank, which was considered the CSO point in the optimization process. In Fig. 7, water flows from the upper to the bottom left portion of the figure.

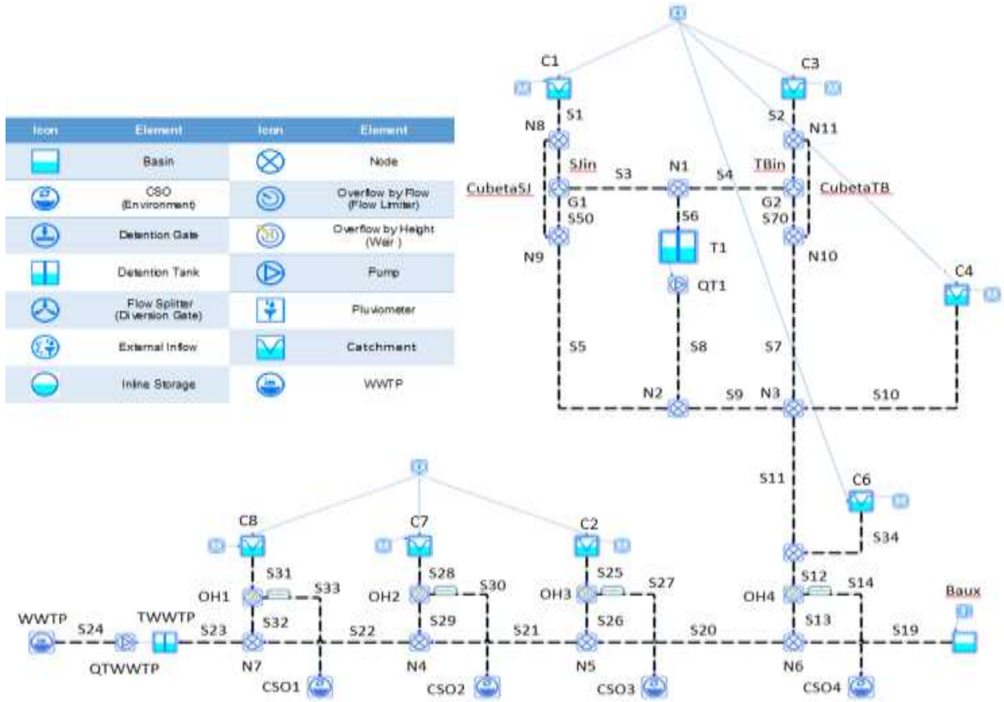


Fig. 7. Diagram of simplified model of Badalona SN.

3.4. Real-time control strategies

Three different scenarios were employed to validate the control approaches using the Badalona case study under different rain events (Fig. 8). Given that the characteristics of rain events can vary tremendously, different time scales were used to capture a wide range of rainfall scenarios. Each one of the three scenarios was simulated using all the compared control approaches: the local control, non-integrated volume-based MPC and the integrated pollution-based MPC. The local control represents the rule-based RTC approach where the control actions are generated by a set of predefined rules provided by the local water operators regarding only hydraulic measurements. The non-integrated volume-based MPC is the MPC approach which only considers the hydraulic dynamics and performance function with CSO volume (exclude the equations 2,3,4,9). The integrated pollution-based MPC is the one proposed in this work, and the integration refers to the WWTP limitations considered during the optimization process.

Scenario 1: *MPC* vs. *Local Control*. This scenario permits the efficiency of the optimization-based approaches to be validated relative to a rule-based *Local Control* approach. Thus, both volume-based MPC and pollution-based MPC are compared to the local control utilized by the water operators, and several conclusions can be extracted about exploiting advanced of the MPC strategies for the SS.

Scenario 2: *Pollution-based MPC* vs. *Volume-based MPC*. The two presented MPC-based approaches are also compared, i.e., the volume-based strategy with respect to the pollution-based procedure. In this study, the benefits of including quality measurements in the optimization process are highlighted.

Scenario 3: *Integrated MPC* vs. *Non-integrated MPC.* As aforementioned, the second difference between the volume-based and the pollution-based strategies consists of the WWTP integration. The volume-based approach does not consider the WWTP limits during the control action computation, whereas the pollution-based MPC indeed considers these limitations to optimize the water input to the treatment facility. Hence, the effects of integrating the WWTP in the control procedure are shown.

The selected rain episodes used for comparisons were:

- **07/05/2016.** An episode with low intensity and duration of rainfall, which is one of the most common types of rainfall events throughout the year.
- **13/02/2016.** A small rain event with an increasing intensity in rain compared with smaller episodes.
- **24/03/2017.** A medium rain event given the accumulated amount of precipitation. These types of rainfall episodes are rare in Badalona.
- **T10.** To challenge the tank management operation proposed by the distinct control approaches, an artificially large rainfall event in terms of both intensity and duration was designed.
- **18/06/2016.** Before validating the proposed control approach, the coordination of the different subsystems in the closed-loop VR simulator was tested using an independent medium rain episode on 18/06/2016.

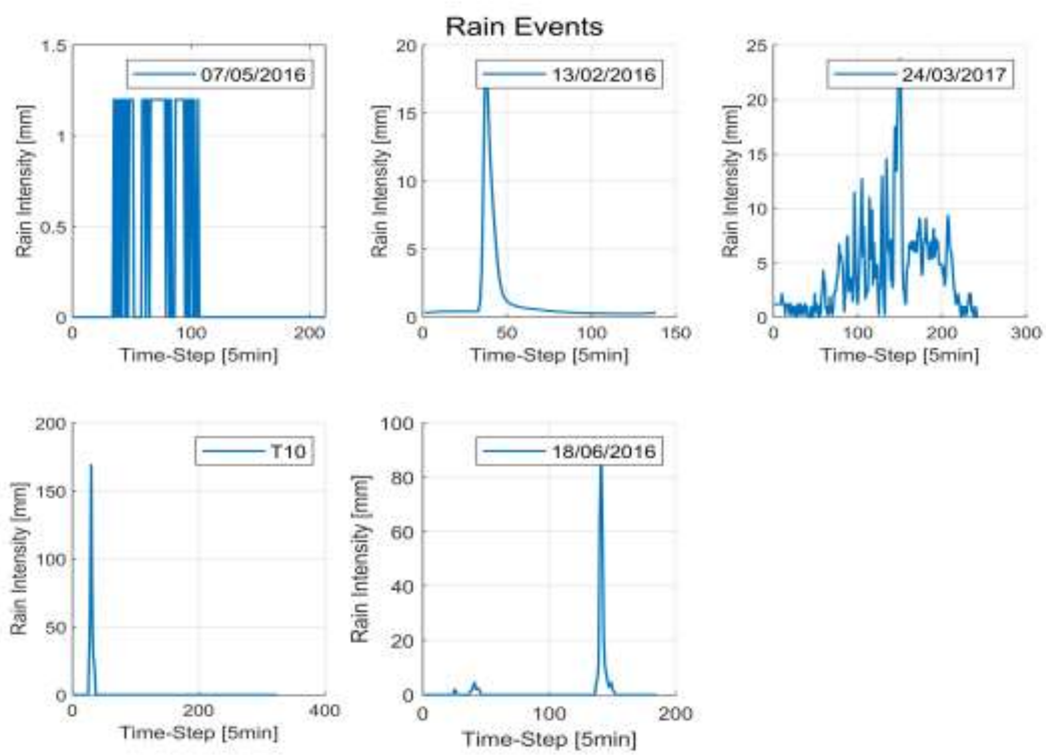


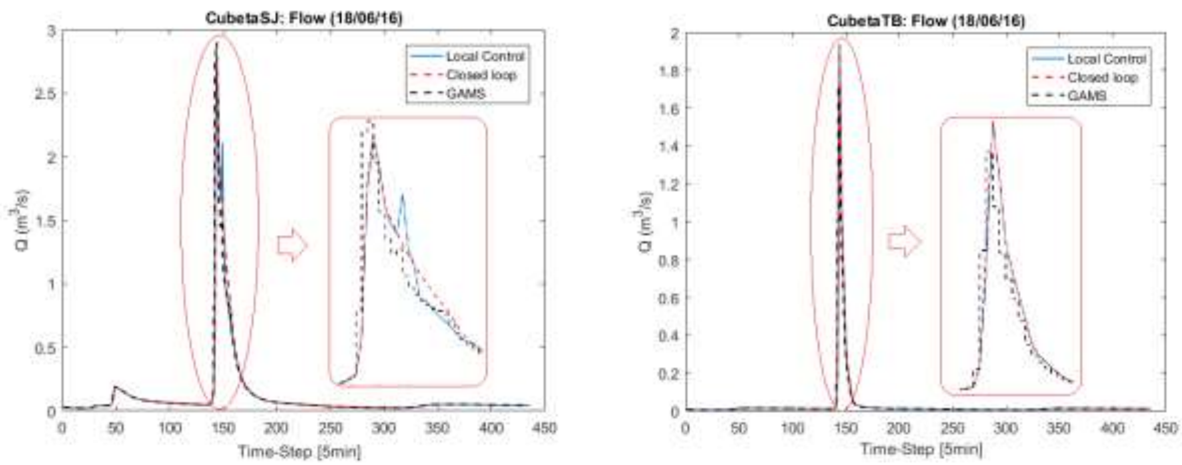
Fig. 8. Rainfall scenarios examined for the Badalona SN.

According to the defined TSS models, the TSS mass in the detention tank primarily considers the mixture behavior [as Eq. (2)]. The transportation at the junction node fits the mass balance

Eq. (4). In addition, TSS transport in the sewer satisfies the linear and instantaneously defined conceptual model in InfoWorks.

1) Closed-loop VR simulator

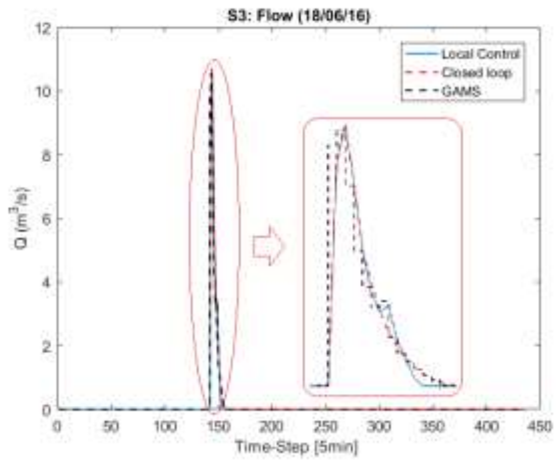
For *Local Control*, water flows and TSS were computed using an independent simulation with embedded rule-based control regulations. For the *MPC*, the flow and TSS dynamics were computed using the MPC models. For the *Closed Loop* modes, the optimal MPC strategies were sent as set points to the actuators in the simulator. Under the rain event of 18/06/2016, the two computed sewer flows during the optimization (*MPC* line) were highly similar with the *Closed Loop* plot (obtained from the results of the detailed model simulation), demonstrating the adequacy of the implemented SS simplified model at the optimizer and the robust operation of the closed-loop procedures (Fig. 9).



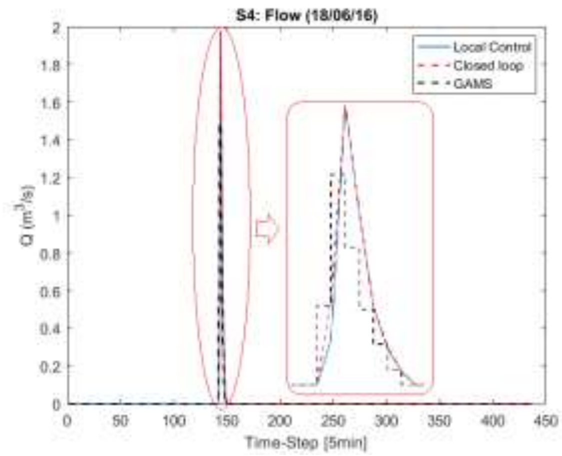
(a) CubetaSJ (b) CubetaTB

Fig. 9. Sewer flows.

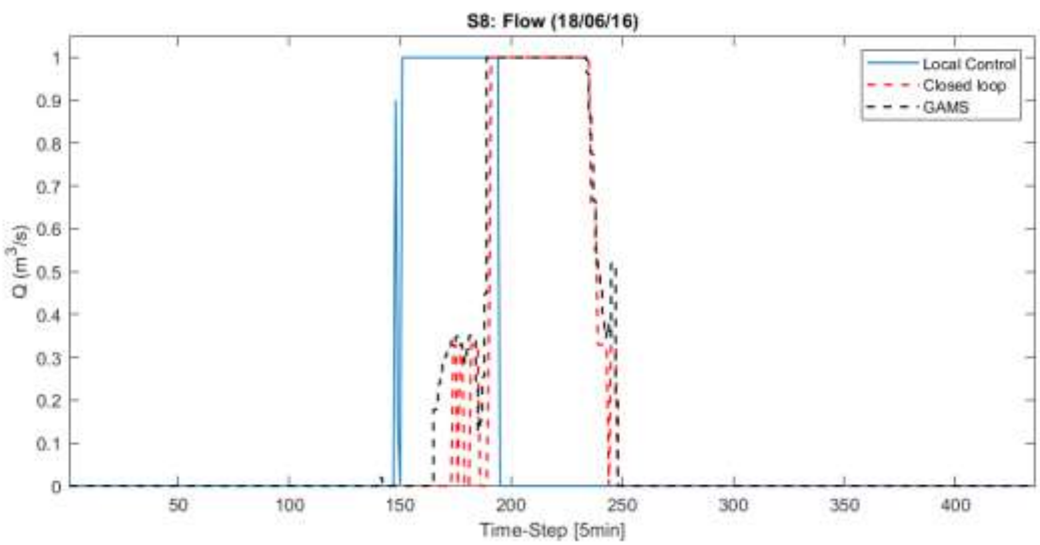
After the optimization process, optimal gate flows were sent as set points to the simulator. Gate flows in the *Closed Loop* were then compared with those computed by the *MPC*. Figure 10 shows that the optimizer and the simulator were working jointly so that the computed set-point flows produced by the optimizer could obtain similar flow values in the detailed network. Figure 10(a) and (b) present the flows at the inlet sewers of the retention tank, while Fig. 10(c) presents the flow pumped out from the tank. The similar behavior of both the *MPC* and the *Closed Loop* reveals the proper functioning of the closed-loop simulation scheme.



(a) S3



(b) S4



(c) S8

Fig. 10. Gate positions and regulator actions in closed loop.

2) Comparison of performance of different control strategies

Comparisons of the implemented control strategies are shown in Table 1. The two considered CSO points in the analysis were CSO4 and CSO5, as the rest of CSOs were passive and thus their flow could not be controlled.

Table 1. Comparison of CSO results.

		Local Control	Volume-based MPC	Pollution-based MPC
07/05/2016	**CSO Volume (m^3)**	8013	7454	7453
	CSO Mass (kg)	7805	7209	7209

13/02/2016	**CSO Volume (m^3)**	23 053	21 075	21 072
	CSO Mass (kg)	10 938	10 063	10 060
24/03/2017	**CSO Volume (m^3)**	145 290	123 510	123 496
	CSO Mass (kg)	26 312	23 761	23 735
T10	**CSO Volume (m^3)**	80 935	76 549	76 804
	CSO Mass (kg)	23 215	19 427	16 196

Scenario 1: MPC vs. Local Control

Table 1 compares the performances of the two proposed MPC approaches with that of a local control strategy. MPC control reduced CSO volume by 7–8.5% for small rain events. This value increased to 15% for the 24/03/2017 episode despite the increased rainfall given that medium-intensity rainfall does not pose major difficulties for tank management. However, the tank operation deteriorated in the T10 event because of the more intense precipitation, resulting in a 5% decrease in CSO volume in the performance of the local control scheme. This reduction was similar for both the volume and pollution-based approaches.

The decrease in pollutant mass released to the receiving body for the three real episodes ranged from 7.6% to 9.7%, and the results were similar for both MPC strategies. The explanation for the difference between the pollution-based and volume-based MPC will be provided in the next scenario. Finally, in scenario T10, there was a 16.3% reduction in the spilled mass when a volume-based strategy was used; in contrast, a pollution-based approach resulted in a 30.2% decrease in spilled mass compared with the local control.

Hence, the proposed MPC approach permitted a reduction in the CSO volume and mass released to the environment relative to the local control strategy.

Scenario 2: Pollution-based MPC vs. Volume-based MPC

Similar volumes were spilled in volume-based control and pollution-based control approaches (the differences in the percentages were lower than 0.1%; Table 1). The performance was also similar for the polluted mass released, except for the T10 episode. In this event, the high intensity and large quantity of rainfall rapidly and completely filled the tank, making it essential to optimize the quality of the stored water. Therefore, pollution-based control is capable of reducing 16.6% of the pollutants reaching the environment relative to the volume-based strategy.

Nevertheless, the efficacy of these approaches is ultimately determined by their integration with WWTPs, as the flow sent to the treatment facility is adjusted to the WWTP capacity in the pollution-based approach but not in volume-based control. Hence, integrating these controls with WWTPs can lead to an improvement in the mitigation of CSO in terms of both spilled volume and mass.

Scenario 3: Integrated MPC vs. Non-integrated MPC

Finally, the integrated and non-integrated MPC controllers were compared. Figures 11–14 highlight the benefits of integration. The first subplot in these figures shows changes in the WWTP primary treatment flow capacity computed by employing the WWTP model, while the second subplot shows changes in the inflow to the WWTP. For the volume-based case, MPC was unaffected by predictions of WWTP capacity given that there was no integration; thus, the influent to the treatment plant was not limited. There was no difference between the integrated and non-integrated approaches in some small rain scenarios (07/05/2016), as the operation of the WWTP never reached its limit because the rainfall intensity in this scenario was not high (Fig. 11).

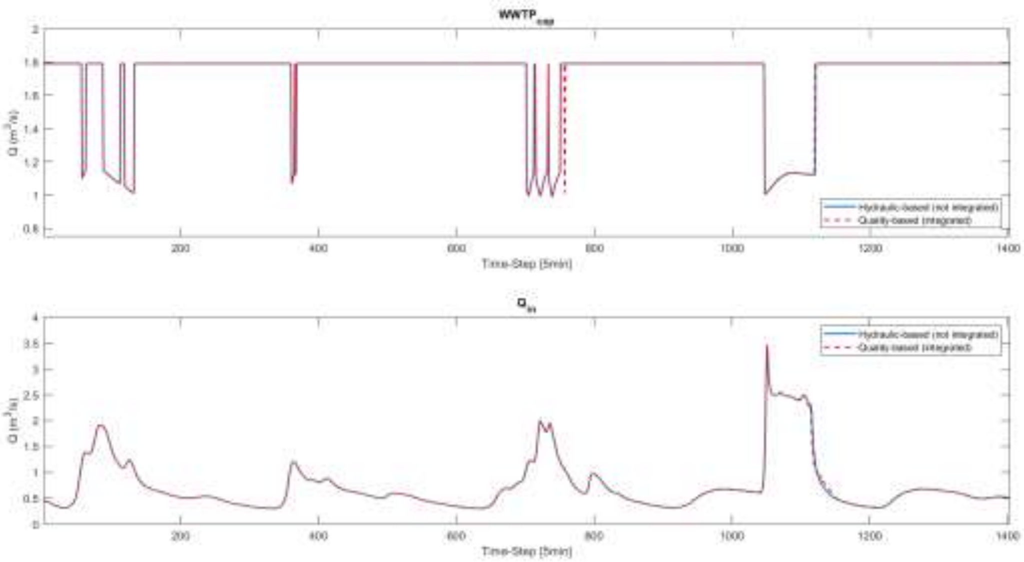


Fig. 11. Calculated WWTP capacity and entrance flow to the plant for the rainfall episode on 07/05/2016.

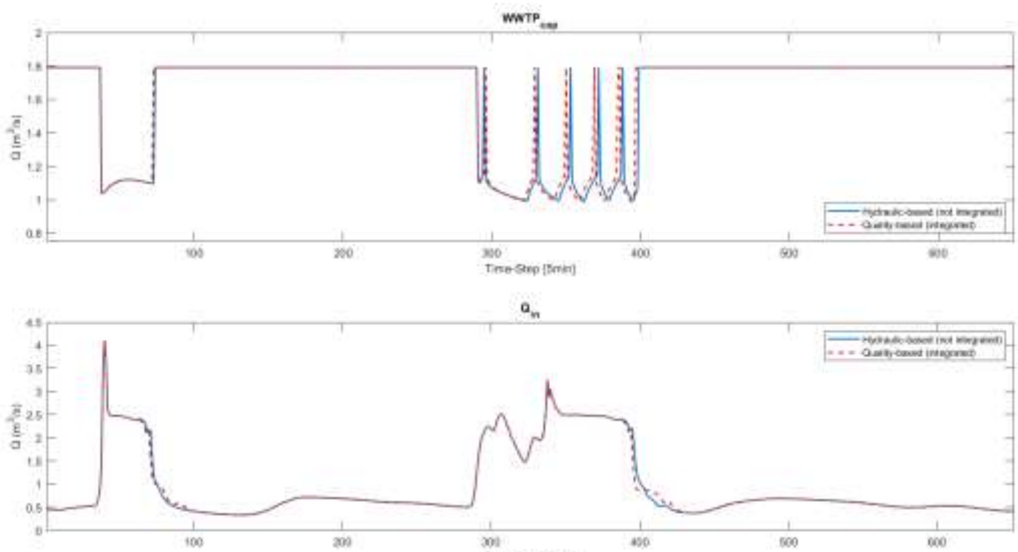


Fig. 12. Calculated WWTP capacity and entrance flow to plant for rainfall episode on 13/02/2016.

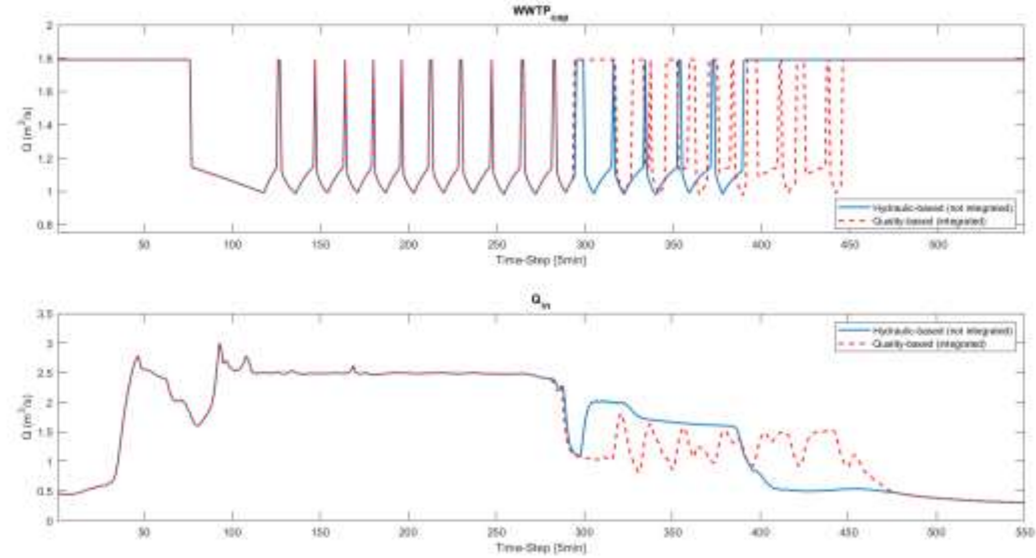


Fig. 13. Calculated WWTP capacity and entrance flow to plant for rainfall episode on 24/03/2017.

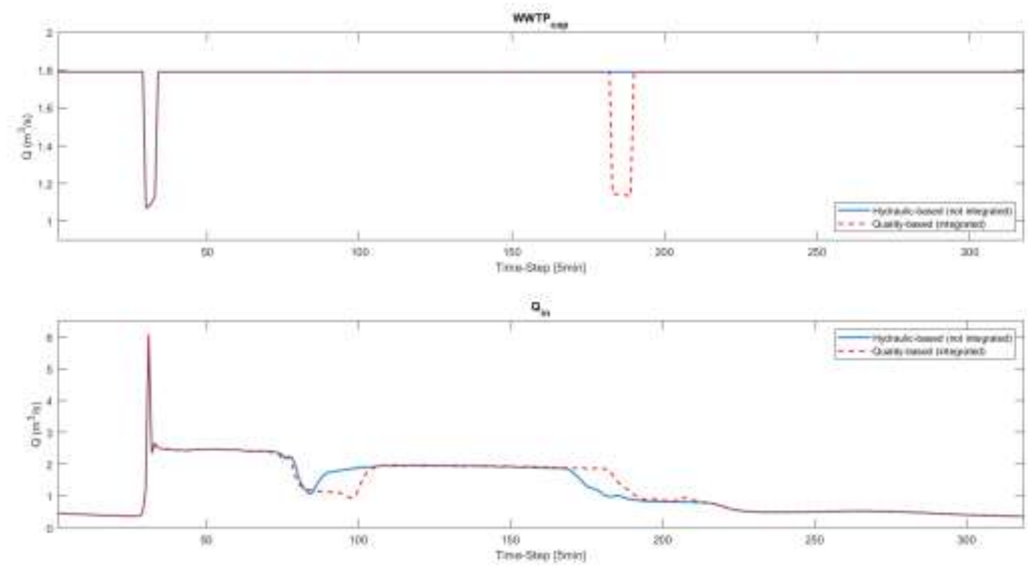


Fig. 14. Calculated WWTP capacity and entrance flow to plant for rainfall episode T10.

However, there were differences in the performance between integrated and non-integrated MPC for the other three rainfall scenarios. The most significant improvements were observed in the rainfall event of 24/03/2017 (Fig. 13).

In the integrated approach, integration reduced the inflow to the WWTP because, since t = 300, the retention tank began to empty such that the flow reaching the plant was mostly affected by the tank outflow. Thus, the WWTP was overall less stressed during its operation. As a result, the WWTP accepted most of the incoming water, thereby reducing the CSO spilling that occurred inside the treatment facility. Because of the difference in the management of the actuators arising from the consideration of WWTP capacity in this rainfall episode, the integrated control reduced the released CSO from the WWTP by 8.1% compared with the non-integrated control.

3) Discussions in results

From Table 1 and Figs. 11–14, several discussions can be obtained.

- Substantial improvements were made by the implementation of MPC approaches comparing to the local control for all of the considered rain episodes. However, this reduction in the volume and mass of CSOs was limited by the low complexity of the topology of the pilot SN. The fact that the network only had one retention tank (with only five actuators) significantly decreases the number of different control strategies that could be implemented among the different RTC approaches, as the degrees of freedom were exclusively derived from the management of the tank-filling and emptying operations.
- Support for the hypothesis that the simple network topology constrained the efficacy of these MPC approaches was confirmed by comparing the volume-based and pollution-based approaches. The incoming water to the tank came from only two basins. Thus, if there was not a significant difference in the concentration of pollutants between the incoming flow from these catchments, there would be no need to include a quality objective in the optimization process. In this case, the volume-based and pollution-based approaches would be equally effective.
- The reduced scope for the action of the control approach also reflects the inability of the network to track WWTP capacity; thus, under low-intensity rains, integration of the SN with WWTP does not significantly affect the control performance. However, the benefits of integration are most evident for high-intensity rainfall scenarios, such as the T10 event (Fig. 14). Therefore, the principal utility of integration is realized during rainfall events that stress the treatment plant.

4. Conclusions

In this work, we proposed an efficient integrated pollution-based RTC approach based on MPC for SSs to mitigate the impacts of pollution from CSO. Moreover, a feedback coordination mechanism has been proposed to integrate the subsystems of SN and the WWTP of SS. The MPC model additionally considered TSS dynamics as a quality indicator. The case study based on the Badalona SS was reproduced using a VR simulation framework under various scenarios. The results showed that the integrated pollution-based MPC approach provides the following conclusions:

1) The MPC strategy can hydraulically reduce the CSO released to the receiving environment comparing to the rule-based local control strategies currently in use;
2) When quality models are factored into the optimization, a mass reduction in CSO can be achieved comparing to only considering the hydraulic model;
3) The integrated control scheme can help in reducing the CSO volume through reading the real-time WWTP capacity.

However, the potential improvements of the proposed approach are affected by several factors: climate; the spatial distribution of the pollution; the available online measurements; the level of automation; the number of detention and storage elements; and the retention volume of rainfall inputs. To continue improving applications of this approach, the following topics require future attention:

1) Certain degree of uncertainties need to be formally incorporated into the optimization module to confirm robustness and accuracy of the control approach.
2) Advantages of digital methods can be exploited into the optimization process with efficient and effective consideration.
3) Another online pilot with different climate is encouraged to be implemented in order to improve the scalability of the proposed approach.

Acknowledgement

The authors wish to acknowledge the support from the European Commission research grant of project LIFE EFFIDRAIN (LIFE14 ENV/ES/000860), from Spanish national project DEOCS (DPI2016-76493-C3-3-R) and the internal project TWINs from the Spanish State Research Agency through the María de Maeztu Seal of Excellence to IRI (MDM-2016-0656). The authors also thank Aigües de Barcelona for their financial and technical support. Considering the fact that data, models and tools used in this research are confidential or commercial, we refer other researchers to contact SUEZ Spain Group (for access to detailed, simplified models; the Closed-loop Simulation Framework software; and the rain data) and Innovyze (for licenses to InfoWorks ICM).

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