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Control-oriented quality modelling approach of sewer networks

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ABSTRACT

A control-oriented quality modeling approach is proposed for sewer networks, which can represent quality dynamics using simple equations in order to optimize pollution load from combined sewer overflows in large scale sewer network in real time. Total suspended solid has been selected as the quality indicator, regarding it is easy to be estimated through measuring turbidity and correlated with other quality indicators. The model equations are independent for different elements in sewer network, which allows a scalable usage. In order to ensure accuracy of the proposed models, a calibration procedure and a sensitivity analysis have been presented using data generated by virtual reality simulation. Afterwards, a quality-based model predictive control has been developed based on the proposed models. To validate effectiveness and efficiency of the modelling and optimization approaches, a pilot case, based on the Badalona sewer network in Spain is used. Application results under different scenarios show that the control-oriented modelling approach works properly to cope with quality dynamics in sewers. The quality-based optimization approach can provide strategies in reducing pollution loads in real time.

1. Introduction

Considering the high concentrations of organic loads, metals and faecal bacteria (Becouze et al., 2009), combined sewer overflow (CSO), which consists a mixture of untreated wastewater and storm water runoffs from sewer networks (SN), can adversely affect the receiving environment (EPA, 2015). In order to protect ecosystem of the receiving body, optimization of a SN in real time to mitigate the pollution impact is cost-effective comparing with infrastructure construction (Joseph-Duran et al., 2015; Schütze et al., 2004; Sun et al., 2017a).

In sewer networks, both hydraulics and hydrology are important factors to be considered for pollution control. So far, most of the approaches focus on the hydraulic aspects, aiming to reduce volume of CSO discharges to the environment. For instance, Joseph-Duran et al. (2014b) optimized CSO volume for a sewer network using a mixed integer linear program. Cembrano et al. (2004); Fu et al. (2010); and Vezzaro et al. (2014) reduced CSO volume through nonlinear approaches. Joseph-Duran et al. (2015) proposed a output-feedback control approach based on hybrid modelling to minimize CSO volume significantly. Moreover, predictive methodologies have also been developed in Lund et al. (2018); and Puig et al. (2009).

Besides hydraulic-based approaches, quality-based objectives can open up new potential for the advanced management of SN (Fu et al., 2020; García et al., 2015; Schütze et al., 2004; Torres-Matallana et al., 2018). Moreover, regarding the increasing availability of sensors in recent years, inclusion of quality variables to the optimization becomes possible (Fu et al., 2010; Hoppe et al., 2011; Lacour and Schütze, 2011). However, it is still a big challenge to develop a model that can describe quality dynamics in SN regarding the complex procedures (Sun et al., 2018; Torres-Matallana et al., 2018). It is also not easy to obtain enough data with good quality to calibrate the models (Fu et al., 2020; Ledergerber et al., 2019).

Nowadays, there exist detailed quality models, i.e. the Ackers White Model (Maciejowski, 2002), Velikanov and the KUL Model (Zug et al., 1998) to describe sediments transportation in SN. There are also well-established tools embed with high fidelity quality equations for

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simulation such as the Storm Water Management Model (SWMM) (Rossman, 2015), MIKE Urban (DHI, 2017), WaterCress (Clark et al., 2002), InfoWorks CS (MWH, 2010) and UrbanCycle (Hardy et al., 2005). These models and tools can represent quality dynamics and processes in SN. But the tools mainly work as simulation platforms, which may not be able to use for optimization. The detailed models are not suitable for optimization either due to the high computational requirement.

Control-oriented quality models which can describe complex dynamics using simple equations (generally linear) are in need for pollution optimization in real time, especially for large scale SN. Lacour and Schütze (2011) proposed a turbidity-based approach, which uses turbidity measurements to generate “realistic” signals at the inflow time series. This approach provides evidence about the potential of quality-based control but does not map the quality dynamics inside SN. Vezzaro et al. (2014) considered relevant water quality indicators (TSS - total suspended solids and ammonia concentration) in a global control of urban catchments through a simple model. Water quality is included in cost functions, which allows to change discharge priority to reduce pollution. However, the quality model does not refer to the sewer network. Torres-Matallana et al. (2018) developed a simplified semi-distributed urban water quality model, EmiStatR, to simulate emissions of pollutants in terms of chemical oxygen demand and NH4 concentrations. However, EmiStatR does not model the quality dynamics in sewer pipe explicitly either.

Under this context, this paper contributes 1) a control-oriented quality modelling approach for different elements of SN. The model equations are developed independently for different elements, which allows scalable use of the models. These models are used to represent complex quality dynamics using simple equations, which can be embedded in real time optimization process. As a first step, TSS has been selected as a relevant quality indicator. This choice takes into account that TSS can usually be correlated with turbidity (Lacour and Schütze, 2011). Similarly, other quality parameters can also be estimated from TSS. 2) A calibration procedure based on data produced by a virtual reality simulator as well as a sensitivity analysis are presented to validate accuracy of the model. 3) Based on the proposed quality models, a quality-based optimization approach has been developed using model predictive control (MPC). 4) In order to validate the modeling and optimization approaches, a real life case study based on the Badalona SN in Spain has been demonstrated using different rain scenarios.

Rest of this paper is organized as follows. In Section 2, the control-oriented quality modelling approach, the calibration procedure and the quality-based optimization scheme are presented. In Section 3, the proposed models are calibrated using data generated by virtual reality simulations. The efficient and effectiveness of the modeling and optimization approaches are demonstrated through the Badalona SN. Conclusions and discussions are provided in Section 4.

2. Methodology

2.1. Modelling approach

The control-oriented modelling approach is used to estimate TSS dynamics in a certain horizon, including the TSS transportation in sewer pipes, TSS deposition and erosion in a detention tank, as well as TSS dynamics in the intersection nodes. There is no direct mathematical association between the models and the physical processes. Each type of element in SN is modelled using separated equations to enhance model scalability for different networks.

Basic hydraulic models are provided firstly as background before introducing the quality models.

In this paper, the italic bold font is used for vectors, italic font represents scalars.

2.1.1. Detention tank

A detention tank is considered as container which collects water based on input and output flows:

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

$$0\leq \boldsymbol{f}(k)\leq \boldsymbol{f}^{max} \tag{2}$$

$$0\leq \boldsymbol{vol}(k)\leq \boldsymbol{vol}^{max} \tag{3}$$

where $\boldsymbol{vol}\in\mathbb{R}^{n_t}$ represents vector for the water volumes $[m^3]$ stored in detention tanks with physical ranges in [0, $\boldsymbol{vol}^{max}$]; $\Delta t$is sampling time [s] and k is time step;$\boldsymbol{f}_{in}=(f_{in}^{1},\quad\dots f_{in}^{n_{in}})\in\mathbb{R}^{n_{in}}$ is the vector of flows into the tank $[m^3/s]$;$\boldsymbol{f}_{out}=(f_{out}^{1},\quad\dots f_{out}^{n_{out}})\in\mathbb{R}^{n_{out}}$ is the vector of flows out of the tank $[m^3/s]$; $\boldsymbol{f}^{max}$ is the vector containing physical or operational limitations of flows. The parameters n_t, n_{in}, n_{out} are numbers of tanks, inflow and outflow branches, respectively.

2.1.2. Controllable actuators

The controllable actuators, gates or pumps, are usually located at the inlet or the outlet of a tank or an inline detention element. Flow from these elements is considered as control variable and bounded by physical and operational constraints:

$$\boldsymbol{u}(k)\leq \boldsymbol{u}^{max}(k) \tag{4}$$

where $\boldsymbol{u}$ is vector of control variables, $\boldsymbol{u}^{max}$ includes the maximum constraints.

2.1.3. Junction node

Mass balance is used for water in and out of a junction node:

$$\sum_{i=1}^{n_{out}}f_{out}^{i}(k)=\sum_{j=1}^{n_{in}}f_{in}^{j}(k) \tag{5}$$

where f_{out}^{i}, $i=1,\dots,n_{out}$ are flows leaving the node; f_{in}^{j}, $j=1,\dots,n_{in}$ are flows into the node.

2.1.4. Overflow

Overflows at CSO locations occur, e.g. by means of weirs, when the capacity of a downstream element (for example, the WWTP) is exceeded by the flow in the upstream element, which is modelled as:

$$\boldsymbol{f}_{cso}(k)=\max\{0,\boldsymbol{f}_{in}(k)-\boldsymbol{maxcap}\ (k)\} \tag{6}$$

$$\boldsymbol{f}_{out}(k)=\boldsymbol{f}_{in}(k)-\boldsymbol{f}_{cso}(k) \tag{7}$$

where $\boldsymbol{f}_{in}$ is the flow vector in the upstream elements, $\boldsymbol{maxcap}$ is the capacity vector of the downstream of the weirs (possibly WWTP inlets or interceptors), $\boldsymbol{f}_{out}$ is the flow vector going to the downstream and $\boldsymbol{f}_{cso}$ is the CSO vector.

2.1.5. Total CSO

The CSO volume released into the receiving environment is computed as:

$$f_{environment}(k)=\sum_{i=1}^{n_{cso}}f_{cso}^{i}(k) \tag{8}$$

where n_{cso} is number of CSO.

Based on these equations, TSS models for different elements in SN are developed as follows:

2.1.6. TSS model for a sewer

A sewer or a collection of sewers in a SN can be assumed as a tank which collects water based on the volumetric difference between input and output flows, as presented in equation (1).

For the outflow vector $\boldsymbol{f}_{out}$, besides complying with the physical constraints of equation (3), the values of $\boldsymbol{f}_{out}(k)$ should also be proportional to the sewer volume $\boldsymbol{vol}(k)$ at the current time step k, which can be represented as:

$$\boldsymbol{f}_{out}(k) = \boldsymbol{c}_{int}\boldsymbol{vol}(k) \tag{9}$$

where $\boldsymbol{c}_{int}$ is a vector of parameters which relates the outflow of a sewer with the water volume stored in it. Here $\boldsymbol{c}_{int}$ works as an intermediate variable in the modelling process.

After combining equations (1) and (9), the following in-out relation can be expressed for a hydraulic transport in a sewer:

$$\boldsymbol{f}_{out}(k+1) = (1 - \boldsymbol{c}_{int}\Delta t)\boldsymbol{f}_{out}(k) + \boldsymbol{c}_{int}\Delta t\,\boldsymbol{f}_{in}(k) \tag{10}$$

where the outflow vector $\boldsymbol{f}_{out}$ at time step $k+1$ is estimated through summing the proportional parts of the outflow vector $\boldsymbol{f}_{out}$ and inflow vector $\boldsymbol{f}_{in}$ at time step k.

Taking into account the correlation between TSS dynamics and the flow rate inside a sewer, similar in-out relation of equation (10) is used to generalize the transport model for the TSS inside sewer with coefficients $\boldsymbol{c}_1$ and $\boldsymbol{c}_2$:

$$\boldsymbol{ss}_{out}(k+1) = \boldsymbol{c}_1\boldsymbol{ss}_{in}(k) + \boldsymbol{c}_2\boldsymbol{ss}_{out}(k) \tag{11}$$

where $\boldsymbol{ss}_{out} \in \mathbb{R}^{n_{out}}$ is the TSS vector [mg/l] out of a sewer, $\boldsymbol{ss}_{in} \in \mathbb{R}^{n_{in}}$ is TSS vector [mg/l] into a sewer; $\boldsymbol{c}_1$ and $\boldsymbol{c}_2$ are parameters need to be calibrated at the range of [0, 1].

2.1.7. TSS model for a detention tank

The TSS model in a detention tank is based on a simple representation of TSS mass evolution considering deposition and erosion processes. According to equation (1), a detention tank has the capacity to collect water volume based on input and output flows. Similarly, TSS mass could also be collected in detention tank based on the difference between mass input and output, as well as the deposition and erosion phenomena.

Taking $\boldsymbol{m} \in \mathbb{R}^{n_t}$ as the vector of total mass [mg] of the suspended solids in the detained water; $\boldsymbol{ss}_{in}$ and $\boldsymbol{ss}_{out}$ are the TSS vectors for the inflows and outflows of a tank; $\boldsymbol{\tau}$ as the transport delay happens in the mixing process, the evaluation of $\boldsymbol{m}$ in the tank can be presented as:

$$\boldsymbol{m}(k+1) = \boldsymbol{\alpha m}(k) + \Delta t(\boldsymbol{f}_{in}(k-\boldsymbol{\tau})ss_{in}(k-\boldsymbol{\tau}) - \boldsymbol{f}_{out}(k-\boldsymbol{\tau})ss_{out}(k-\boldsymbol{\tau})) \tag{12}$$

where $\boldsymbol{\alpha}$ is a vector representing mass deposition and/or erosion processes and should be calibrated using values between 0 and 10 for each tank; $\boldsymbol{\tau}$ represents non-negative integer of transportation delays. The values of $\boldsymbol{\alpha}$ in the range of [0, 1] describes the deposition process while the values at the range of [1, 10] represents the erosion process. Here the erosion constraint 10 is only an estimated maximal constraint. Bigger constraint can be used in real implementations with stronger erosion. In order to achieve a model with accuracy, the items in equation (12) might be modified by considering more independent coefficients:

$$\boldsymbol{m}(k+1) = \boldsymbol{\alpha m}(k) + \Delta t\boldsymbol{\beta f}_{in}(k-\boldsymbol{\tau})\boldsymbol{ss}_{in}(k-\boldsymbol{\tau}) - \Delta t\boldsymbol{\gamma f}_{out}(k-\boldsymbol{\tau})ss_{out}(k-\boldsymbol{\tau}) \tag{13}$$

where $\boldsymbol{\beta}, \boldsymbol{\gamma}$ are positive vectors to be calibrated for each tank using values between 0 and 10.

Assuming in the detention tank, TSS is the same throughout the stored water, which is also TSS at the tank outlets is (valid only for $\boldsymbol{vol} > 0$):

$$\boldsymbol{ss}_{out}(k+1) = \frac{\boldsymbol{m}(k+1)}{\boldsymbol{vol}(k+1)} \tag{14}$$

2.1.8. TSS model for a junction node

A junction node is considered as the element where volume and suspended solid mass are split or merged based on mass balance. Take a junction of two incoming sewers with one downstream sewer as an example, when suspended solid mass reaches a junction node, the dynamics of TSS is modelled as:

$$e_{out}(k)ss_{out}(k) = e_{in}^1(k)ss_{in}^1(k) + e_{in}^2(k)ss_{in}^2(k) \tag{15}$$

where e_{out} is the coefficient for the TSS output flow, e_{in}^i is coefficient for the *i-th* TSS input flow. They are positive parameters need to be calibrated in range of [0, 10]. To give the same weight for each coefficient for the multi-input junction nodes, each coefficient should be close to 1.

2.2. Calibration procedure

The proposed quality models should be calibrated before application. A virtual reality simulator of SN is used to produce data sets required by the calibration process, which has been designed and calibrated based on real life plants and measurements. So that the quality processes can be represented correctly by the simulator. As described in the modelling approach, water flows, TSS in and out of a sewer are the only information required by the calibration. Different historical rainfall data are used as inputs to the simulator to generate the required information.

2.2.1. Calibration for sewer model

According to equation (11), $\boldsymbol{c}_1, \boldsymbol{c}_2$ are parameters need to be calibrated.

Defining $\widehat{\boldsymbol{ss}}_m$ as the observed TSS. The observed TSS and flow values at previous time step are $\widehat{\boldsymbol{f}}_{in}, \widehat{\boldsymbol{f}}_{out}, \widehat{\boldsymbol{ss}}_{in}, \widehat{\boldsymbol{ss}}_{out}$. The parameters of $\boldsymbol{c}_1, \boldsymbol{c}_2$ are calibrated through minimizing difference between the observed TSS and the modelled TSS:

$$(\boldsymbol{c}_1^*, \boldsymbol{c}_2^*) = \underset{(\boldsymbol{c}_1, \boldsymbol{c}_2)}{\operatorname{argmin}} \left(\sum_{k=1}^{N} \left(\widehat{\boldsymbol{ss}}_m(k) - \boldsymbol{c}_1\widehat{\boldsymbol{ss}}_{in}(k-1) - \boldsymbol{c}_2\widehat{\boldsymbol{ss}}_{out}(k-1) \right)^2 \right)^{½} \tag{16}$$

where N is duration of the event.

2.2.2. Calibration for tank model

The parameters $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\tau}$ need to be calibrated for the tank model. The sedimentation and erosion phenomena are represented through setting values at different ranges for the calibrated parameters. When the parameter takes value from 0 to 1, it means the sedimentation happens, when setting values at the range of [1, 10], erosion happens. There may have sedimentation and erosion two processes happen together in reality, however, we consider in this work only one process happens at each time.

According to equations (1), (13) and (14), the parameters of $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\tau}$ are calibrated as:

$$(\boldsymbol{\alpha}^*, \boldsymbol{\beta}^*, \boldsymbol{\gamma}^*, \boldsymbol{\tau}^*) = \underset{(e_{out}^*, e_{in}^{1*}, e_{in}^{2*})}{\operatorname{argmin}} \left(\sum_{k=1}^{N} \left(\widehat{\boldsymbol{ss}}_m(k) - \frac{\boldsymbol{\alpha m}(k-1) + \boldsymbol{\beta}\Delta t\widehat{\boldsymbol{f}}_{in}(k-\tau-1)\widehat{\boldsymbol{ss}}_{in}(k-\boldsymbol{\tau}-1) - \boldsymbol{\gamma}\Delta t\widehat{\boldsymbol{f}}_{out}(k-\boldsymbol{\tau}-1)\widehat{\boldsymbol{ss}}_{out}(k-\boldsymbol{\tau}-1)}{\boldsymbol{vol}(k-1) + \Delta t\left(\widehat{\boldsymbol{f}}_{in}(k-1) - \widehat{\boldsymbol{f}}_{out}(k-1)\right)} \right)^2 \right)^{½} \tag{17}$$

The initial mass ($\boldsymbol{m}(0)$) and water volume ($\boldsymbol{vol}(0)$) at the tank can be set as 0 or other initial values read from the simulators.

2.2.3. Calibration for junction model

The following equation should be met during calibration while e_i and e_j takes value from [0 10] but better as close as possible to 1:

$$\left(e_{out}^{*}, e_{in}^{1*}, e_{in}^{2*}\right) = \underset{\left(e_{out}^{*}, e_{in}^{1*}, e_{in}^{2*}\right)}{\operatorname{argmin}} \left(\sum_{k=1}^{N} \left(\widehat{ss}_{m}^{i}(k) - \frac{e_{in}^{1}\widehat{f}_{in}^{1}(k)\widehat{ss}_{in}^{1}(k) + e_{in}^{2}\widehat{f}_{in}^{2}(k)\widehat{ss}_{in}^{2}(k)}{e_{out}\widehat{f}_{out}(k)} \right)^{2} \right)^{½} \tag{18}$$

2.2.4. Performance evaluation

In order to evaluate the proposed modelling approaches, Nash Sutcliffe model efficiency coefficient (NSE) (Nash and Sutcliffe, 1970), which is sensitive to pollutograph peaks, and the Normalized Root Mean Square Error (NRMSE), a standard deviation of prediction errors (Functional, 2005) are selected .

2.2.4.1. NSE index. Defining average of the observed TSS as $\overline{\widehat{ss}_m}$, which can be computed as:

$$\overline{\widehat{ss}_m} = \frac{\sum_{k=1}^{N}\widehat{ss}_m(k)}{\sum_{k=1}^{N}k} \tag{19}$$

Then performance in terms of NSE for the proposed models can be computed as:

$$\boldsymbol{NSE}_{ss} = 1 - \frac{\sum_{k=1}^{N}\left(\boldsymbol{ss}_{out}(k) - \widehat{\boldsymbol{ss}}_m(k)\right)^2}{\sum_{k=1}^{N}\left(\widehat{\boldsymbol{ss}}_m(k) - \overline{\widehat{\boldsymbol{ss}}_m}(k)\right)^2} \tag{20}$$

The value of $\boldsymbol{NSE}_{ss}$ range from $-\infty$ to 1. If $\boldsymbol{NSE}_{ss}$is equal with 1, it corresponds to a perfect match of the model. If $\boldsymbol{NSE}_{ss}$ can get value between 0.5 and 0.65, that indicate the model is sufficiently good to be used (Sun et al., 2017b).

2.2.4.2. NRMSE index. The value of $\boldsymbol{NRMSE}_{ss}$ is computed using equation (21):

$$\boldsymbol{NRMSE}_{ss} = \frac{1}{\max\left(\widehat{SS}_m(k)\right) - \min\left(\widehat{SS}_m(k)\right)} \sqrt[2]{\sum_{k=1}^{N}\frac{\left(ss_{out}(k) - \widehat{ss}_m(k)\right)^2}{N}} \tag{21}$$

In general, is expressed as a percentage, where the lower value indicate less errors.

2.2.5. Practical implementation

Water quality measurements inside the SN or appropriate estimations are indispensable for model calibration. For sewer elements, these data may be estimated using a number of real turbidity sensors, complemented by TSS estimations of a detailed model. For the case of detention tanks, TSS measurements or estimations at the tank inlet and output are required. The sensors for the tank inlet and output may not be available in the real system and in the detailed quality simulators, this information is not readily available. In this case, we do not have reliable data for the TSS tank model calibration, and we suggest to use an approximation of the TSS in detention tank with perfect mixture hypothesis for the total mass as a conservative alternative. Then, the model coefficients for the tank model $(\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\tau})$ would be $(\mathbf{1}, \mathbf{1}, \mathbf{1}, \mathbf{0})$.

2.3. Quality-based optimization using MPC

MPC has been selected as the optimization scheme because of its capacity to generate optimal control strategies especially for a complex network, as proved in García et al. (2015); Joseph-Duran et al. (2015); Pleau et al. (2005); Puig et al. (2009); Schütze et al. (2003); and Sun et al. (2020). The principal goal of the quality-based MPC optimization approach is minimizing both volume and pollutant load of CSO through efficient operation of controllable actuators (pumps, gates, etc.), taking into account hydraulic and quality models defined previously.

2.3.1. Optimization control problems

The quality-based MPC optimization is defined using a state-space discrete-time model:

$$\min_{\boldsymbol{u}(k)} \boldsymbol{J}(\boldsymbol{k}) \tag{22a}$$

s.t.:

$$\boldsymbol{x}(k+1) = f(\boldsymbol{x}(k), \boldsymbol{u}(k), \boldsymbol{d}(k)) \tag{22b}$$

$$h(\boldsymbol{x}(k), \boldsymbol{u}(k), \boldsymbol{w}(k)) \geq 0, \tag{22c}$$

$$g(\boldsymbol{x}(k), \boldsymbol{u}(k), \boldsymbol{w}(k)) = 0, \tag{22d}$$

$$\boldsymbol{x}_{min} \leq \boldsymbol{x}(k) \leq \boldsymbol{x}_{max}, \tag{22e}$$

$$\boldsymbol{u}_{min} \leq \boldsymbol{u}(k) \leq \boldsymbol{u}_{max}, \tag{22f}$$

where $\boldsymbol{x}(k)$ is state vector represents water volume and mass in all tanks; $\boldsymbol{u}(k)$ is the controlable vector of gate flows; $\boldsymbol{d}(k)$ is disturbance vector related to rain intensity and runoff. The functions $h(\cdot)$ and $g(\cdot)$ include constraints, $\boldsymbol{u}_{min}, \boldsymbol{u}_{max}, \boldsymbol{x}_{min}, \boldsymbol{x}_{max}$are physical limits of vectors.

2.3.2. Objective function

The objective function is a mathematical representation of the operational goals, including CSO discharges minimization $\boldsymbol{J}_{cso}(k)$, pollutant loads (TSS mass) from CSO minimization $\boldsymbol{J}_m(k)$ and WWTP usage maximization $\boldsymbol{J}_{wwtp}$, expressed as:

$$\boldsymbol{J}(k) = \sum_{k=1}^{N}\left[a_{cso}\boldsymbol{J}_{cso}(k) + a_m\boldsymbol{J}_m(k) + a_{wwtp}\boldsymbol{J}_{wwtp}(k)\right] \tag{23}$$

where a_{cso}, a_m, a_{wwtp} are weights of different objectives which can be generated through Pareto front computation for the multi-objective optimization problem in (23) or in practice, priorities of these items are mainly manipulated by the system operators in order to adjust to different situations (Lund et al., 2018; Toro et al., 2011).

Fig. 1. The Badalona SN.

2.3.3. Control optimization setup

The quality-based MPC optimization produces control actions inside the prediction horizon of H, however, only the first solution is applied into simulation as set-points to validate the control actions without disturbing the real plant. In order to compensate uncertainty produced by the conceptual models, in each time step, the new system state (e.g. the tank volume, mass, etc.) of simulator is used as initial values for the next step optimization using MPC. This interaction between the controller and simulator is the so called closed-loop optimization scheme, which has been explained in detail in (Romero-Ben et al., 2019; Sun et al., 2015).

Table 1
Rain events.

RAIN EVENT	I_{20}	I_{60}	START TIME	END TIME	PREVIOUS DRY DAYS	RAIN INTENSITY
25/03/2017	39.6	24.6	08:20 24/03	06:35 26/03	20	Medium
22/07/2016	31.5	18.3	08:25 22/07	21:45 23/07	53	Small
22/08/2014	42.6	17.8	09:30 22/08	22:30 23/08	20	Big
18/06/2016	60.3	24.4	03:40 18/06	16:25 19/06	20	Very big
T10	110.5	52.9	00:00 01/01	03:00 02/01	10	Strong

3. Case study

3.1. Badalona sewer network

Badalona is a city at the east of Catalonia (Spain) facing to the Mediterranean Sea. Affected by the Mediterranean climate, 50% of the rainfall occurs at two or three heavy rainfall events in summer and autumn, which used to generate CSOs to the beach of Badalona. As shown in Fig. 1, the Badalona SN (blue color) includes one detention tank (blue cylindrical). The WWTP is located on the side of the coast. Along the coast locates the outfall points (red color) from where the CSOs are released. Three rain gauges P1, P2, P3 are distributed in different area of this network.

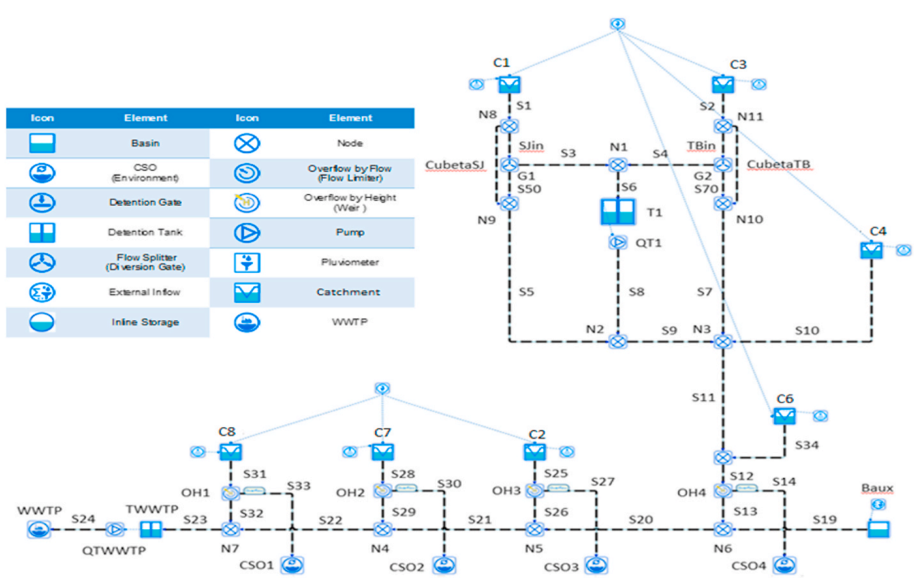

Fig. 2. Simplified Badalona SN.

The Badalona SN has been simulated in InfoWorks Integrated Catchment Modelling (InfoWorks ICM) (MWH, 2010). Full 1D Saint Venant equations (Joseph-Duran et al., 2014a) is used in InfoWorks to solve the hydraulic dynamics. Velikanov model (Zug et al., 1998) is used to describe dynamics of TSS in a detention tank. The TSS in the sewer is linear and instantaneous.

To compute the quality-based MPC optimization, the Badalona SN has been conceptualized as Fig. 2 with a clear layout includes 7 catchments (C1, C2, C3, C4, C6, C7, C8) and a basin (Baux) connected by 35 links and 5 outfalls. There are 2 gates (G1, G2) operate water input to the detention tank, one pump station (QT1) to empty the detention tank and another pump (QTWWTP) to schedule flows towards the WWTP. The conceptualization process can be found in (Martínez et al., 2019).

3.2. Quality modelling calibration

To generate calibration data from the simulator, 4 real rain events and a synthetic scenario T10 have been applied (Table 1). The real rainfall was measured in terms of 5-min interval from the year 2014–2017. The selected rains are the representative events with different characteristics (*small, medium, big, very big*). The synthetic scenario T10 was designed as a *strong* rainfall of 10-year return period following a rainfall distribution prepared by Alternating Block Method (Ghazavi et al., 2017). In Table 1, start and end time of the rain are in format of HH:MM DD/MM. Previous dry days are given for each scenario. Moreover, $\boldsymbol{I}_{20}, \boldsymbol{I}_{60}$ which represent precipitation intensities considering 20-min and 60-min time steps are provided to describe the intensity.

3.2.1. Model for sewer

To illustrate the TSS sewer model, the sewer ***S2*** (as shown in Fig. 2) is selected as an example to calibrate the proposed sewer model. Among the 5 rain events, the first three of them (*25/03/2017, 22/07/2016, 22/08/2014*) are used for calibration, while the rest two events (*18/06/2016, T10*) are used for validating the models produced by the calibration.

Fig. 3 includes the calibration result of ***S2*** for the rain event *22/07/2016,* which has more than 89% *NSE* fitting accuracy. The *NRMSE* index is less than 0.03%, which indicates very few errors. The validation results of this calibrated model using rainfalls *18/06/2016* and *T10*, where more than 85% *NSE* fitting accuracies are still achieved, the *NRMSE* errors are less than 0.01%, as shown in Fig. 3 as well.

Table 2 presents more details about the calibration and validation results, which includes the calibrated parameters and performance in each case. Considering both the calibration and validation performance in *NSE* are better than 80%, the *NRMSEs* are less than 0.1%, the proposed TSS model for the sewer can represent the TSS dynamics well at the Badalona pilot.

Considering the fact that, there exists uncertainties for using conceptual models. In order to get a better knowledge about the uncertainty influence, sensitivity analysis is carried out. The following steps are applied into analysis, which firstly fix **c**1, and add **c**2 with 0.02, 0.04, 0.06 individually; then fix **c**2*,* and minus **c**1 with 0.2, 0.4, 0.6 separately, considering the different order of magnitude in **c**1 and **c**2. Fitting results are provided with *25/03/2017* as representative scenario. The results at Figs. 4–5 show that the uncertainty of **c**1 which is coefficient of the TSS input at the previous time step, affects more about the TSS sewer than the coefficient of the previous TSS output **c**2. Furthermore, higher intensity rainfall period is affected more when modifying the calibration parameters. However, the trends of the curves can always be captured.

3.2.2. Model for junction node

The junction node model is validated through a downstream node ***N6*** of the Badalona SN, which has two input branches ***S13, S19*** and one output ***S20*** according to equation (19):

$$\widehat{ss}_m^{20}(k) = \frac{e_{in}^1 \widehat{f}_{in}^{13}(k)\widehat{ss}_{in}^{13}(k) + e_{in}^2(k)\widehat{ss}_{in}^{19}(k)}{e_{out}\widehat{f}_{out}^{20}(k)} \tag{24}$$

Regarding the coefficient constraints, for the node N6, the optimal calibrated value for e_{in}^1, e_{in}^2 and e_{out} are near **1**, which represents suspended solids at the junction node follow mass balance.

Fig. 6 list the calibration results of ***N6*** based on the *22/07/2016*, where the TSS output for the ***S20*** computed from the model (15) is quite similar with the observed one from simulator using the value of 1 for e_1 and e_2. The result confirms that, the suspended solids in the junction node ***N6*** fits well mass balance equation with very few deviations at the Badalona pilot.

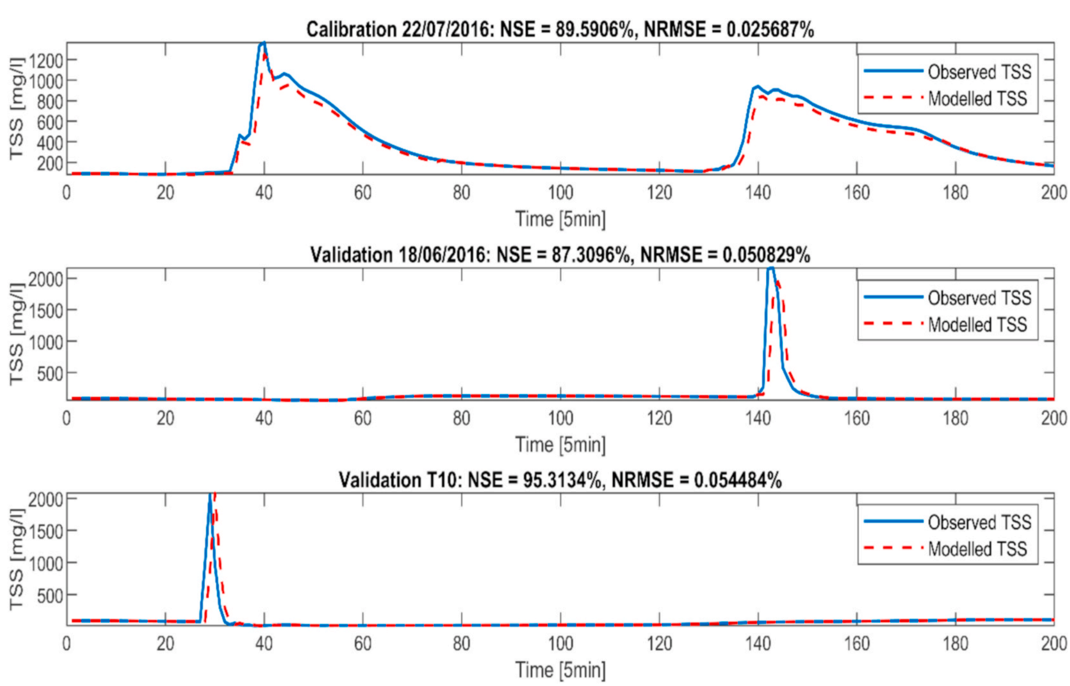

Fig. 3. Calibration and validation results.

Table 2
Calibration and validation results.

CALIBR./VALID.	C2	C1	NSE	NRMSE	18/06/2016		T10	
25/03/2017	0.04	0.95	93%	0.02%	87%	0.05%	95%	0.05%
22/07/2016	0.08	0.99	90%	0.03%	86%	0.04%	93%	0.07%
22/08/2014	0.08	0.90	76%	0.04%	88%	0.03%	94%	0.06%

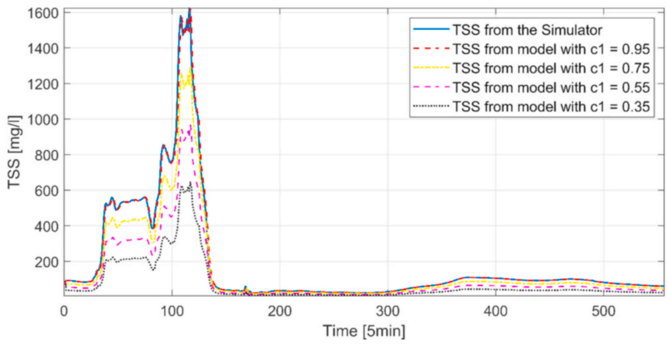

Fig. 4. Sensitivity Analysis for rainfall 25/03/2017 when fixes *c2* as constant.

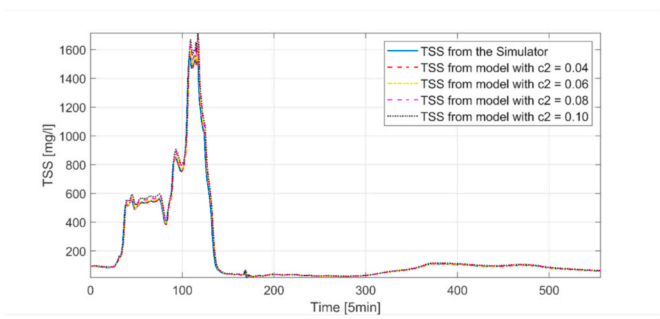

Fig. 5. Sensitivity Analysis for rainfall 25/03/2017 when fixes *c1* as constant.

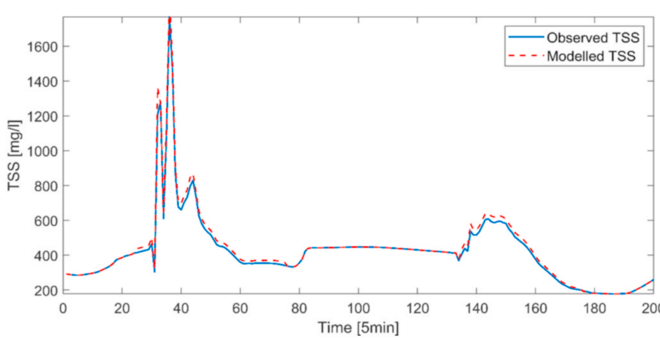

Fig. 6. Junction model calibration for N6 at rain 22/07/2016.

Table 3
Quality models used in RTC application.

RAIN EVENT	RAIN INTENSITY	C2	C1	α	β	γ	τ
25/03/2017	Medium	0.04	0.95	1	1	1	0
22/07/2016	Small	0.08	0.99				
22/08/2014	Big	0.08	0.90				
18/06/2016	Very big	0.11	0.89				
T10	Strong	0.01	0.99				

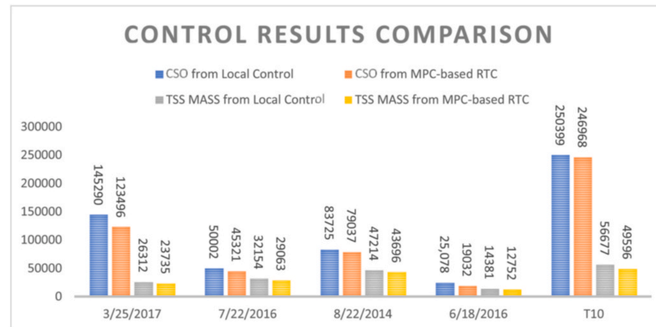

Fig. 7. Control results comparison in terms of CSO and TSS MASS (m^3).

Table 4
Optimizer and simulator configuration.

GAMS Optimizer		InfoWorks Simulator	
# variables	970	***# nodes***	14,285
# equations	981	***# links***	**15,055**
#compute time	1.32s	31.31s	
#CPU			

3.3. Optimal control application

In order to demonstrate effectiveness of the proposed quality modelling approaches, quality-based optimization approach using MPC is applied. In each iteration, MPC optimizes the defined objective function at equation (23) using the proposed quantity and quality equations to produce optimal operation strategies for the Badalona pilot. The GAMS optimization library (Rosenthal, 2013) is used as a solver.

The quality-based optimization approach has been validated using rain episodes of *25/03/2017, 22/07/2016, 22/08/2014, 18/06/2016* and a synthetic scenario *T10*. The calibration results for the quality models listed in Table 3 are used. The optimization results in items of CSO and TSS mass are compared with the ones produced by *Local Control* strategies which generate operation actions based on a set of predefined rules regarding hydraulic measurements.

Fig. 7 provides the CSO volume and mass comparisons between *Local Control* and *MPC-based* optimization under different rainfall events. The results confirm that, both CSO volume and mass pollution released to the environment are reduced after considering a MPC-based optimization with quality models. For some rain scenarios, more than 20% CSO reduction and more than 12% TSS pollution are reduced, which represent a significant improvement for the receiving water and environment. Furthermore, considering the optimization results are affected a lot by the network topology as well as the rainfall intensity, a more noticeable difference between the volume-based strategies and the quality-based one might be observed in scenarios with very different quality indicator values at the tank inlets. Similarly, in network configurations with more detention tanks and/or actuators, more degrees of optimization and large improvement potentials exist for quality-based MPC optimization.

To confirm that add quality models into optimization can still meet real-time requirements, Table 4 summarizes computation loads for both the controller and simulator:

It is clear that the mean computation time of one step optimization is much smaller than one step simulation, which make real-time optimization possible, also in a large scale network.

4. Conclusion and discussion

This work proposed a control-oriented quality modelling approach for TSS in SN, which open up new potential for optimization of pollution load from CSO in large scale network in real time. The calibration and validation results in the Badalona SN confirms applicable of the models in a realistic and accurate way from all the available sources (more than 80% *NSE* and less than 0.1% *NRMSE*). The sensitivity analyze for the TSS model in a sewer shows that the TSS input coefficient affects more than the coefficient of the previous TSS output. The peak time with higher intensity rainfall period is more likely to be affected with more inaccuracy. This peak time cannot be managed from the sediment transport formulas because it is related to the hydraulic behavior (where a peak time difference also exists). To improve the models, much more real data to accurately calibrate TSS behavior is needed. Moreover, online sensors are also advised to properly capture the TSS evolution in wet weather.

A quality-based MPC optimization is also presented after considering both the quality and hydraulic models. Comparing with the current local control, in some rain scenarios, the quality-based MPC optimization approach can achieve more than 20% reduction in CSO volume and more than 12% TSS reduction in released pollution. The potential improvement of the optimization approach could be different in different pilots. The considered quality indicators, the available measurements, magnitudes of CSOs, intensity of rainfalls, as well as the physical topology of the network can all affect the application effectiveness. To get better optimization results, more integration with other catchments and treatment plants in the watershed from a global perspective, or even with the supply network should provide more possibilities and potentials.

5. Credit author statement

Congcong Sun: Conceptualization, Methodology, Investigation, Validation, Original draft preparation, Reviewing and Editing; Luis Romero Ben: Software, Writing- Reviewing and Editing; Eduard Muñoz Craviotto: Software, Reviewing and Editing. Vicenç Puig: Methodology, Supervision, Reviewing and Editing. Bernat Joseph-Duran, Jordi Meseguer, Gabriela Cembrano, Montse Martinez and Puentes Ramon Guasch Palma: Methodology, Supervision, Reviewing and Editing, Project administration, Funding acquisition.

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.

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