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Nonlinear optimization for improving the operation of sewer systems: the Bogotá Case Study.

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Abstract: Sewer systems are considered as complex large-scale systems that traditionally collect and transport stormwater and sanitary sewage out from urban areas. Each subsystem is in itself composed of a large number of elements with time-varying behavior, exhibiting several operating modes and subject to changes due to external conditions and operational constraints. Sewer systems are mainly operated using pumping stations and pollutants are removed from sewage by treatment plants before water is released into the environment. When a sewer overflow occurs, e.g., caused by a strong rainfall, sewage is discharged directly into the environment with some dilution but without treatment. An efficient use of storage capacities and pumping stations can help to minimize the environmental pollution caused by sewer overflows. In this paper a nonlinear predictive control approach is presented to improve the operation of sewer systems. To deal with the nonlinear and non-differentiable features of the used prediction model, a pattern search method is proposed to solve the underlying optimization problem. The technique proposed is implemented on a part of the sewer system of Bogotá, Colombia. Simulation results illustrate the potential of the approach.

Keywords: model predictive control, nonlinear optimization, pattern search, City Drain toolbox.

1 INTRODUCTION

Urban wastewater systems consist principally of the sewer system (including combined sewer overflows (CSO) structures, pumping stations, stormwater channels, etc.), the wastewater treatment plant (WWTP), and the receiving system (normally rivers). Sewer systems are large-scale water transportation systems that span complete urban areas. On one hand, they are the complementary part of water distribution systems by draining wastewater (produced by domestic usage and industrial facilities) out from urban areas up to wastewater treatment plants that remove physical, chemical, and biological contaminants, before releasing the wastewater into the natural environment. On the other hand, sewer systems prevent stormwater arising from excessive rainfall to flood into streets by draining water up to neighboring rivers. Urban drainage systems handle two types of water - wastewater and stormwater [Butler and Davies, 2004]. There are two traditional types of urban sewer systems, combined and separate. The combined system coveys wastewater and stormwater in a single pipe, allowing discharges into the receiving water body from combined sewer overflows when the capacity of the system is exceeded. While, in a separate system, stormwater is separately transported by storm sewers and discharged, normally without treatment, into the receiving water system. An efficient operation of sewer systems is of crucial importance to minimize the amount of pollutants that is spilled into the environment. Cities in areas that experience heavy rainfall as well as coastal towns that regularly experience storms and cities with sewer systems with limited capacity are hereby of major concern. Moreover global climate changes cause more intense periods of precipitation than before [Intergovernmental Panel on Climate Change, 2007], increasing the risk of floods and overflows. In particular combined sewer overflows can hereby cause serious water pollution problems as untreated sewage is then spilled into the environment. Sewers are frequently operated using pumping stations to control the flows in the system. This operation is generally carried out manually. When storage facilities are present, they allow to store sewage during a storm. When the storm is over, sewage is pumped out of the storage facilities and sent to a wastewater treatment plant. An efficient operation of the pumping stations and an efficient use of the storage facilities can minimize the sewer overflows, improve the use of the wastewater treatment plant, and consequently reduce the uncontrolled spill of pollutants. Control systems for sewer netwkorks has been developed since late 1990s with [Marinaki and Papageorgiou, 1997], [Marinaki and Papageorgiou, 2005] and [Pleau et al., 2005]. This paper presents an approach that propose a novel nonlinear predictive control for improving the operation of sewer systems using a pattern search optimization technique. The predictive control is based on a nonlinear simulation model instead of a linear model usually used in predictive control problems. This work is in line with recent innovative works in modeling, simulation, and control of urban wastewater systems. These works have a model-based framework, optimal control features, and real-time computation concerns in common [Schütze et al., 2004; Marinaki and Papageorgiou, 2005]. Within the framework of model predictive control (MPC) strategies, which have attracted the attention for over a decade for their ability to handle explicitly economic objectives as well as operational constraints, there are works as e.g., [Gelormino and Ricker, 1994; Cembrano et al., 2004; Ocampo, 2007; Fiorelli and Schutz, 2009]. Recent works include MPC with fault detection [Ocampo, 2007], MPC using a multi-goal objective function [Fiorelli and Schutz, 2009], and MPC based on hybrid dynamical models [Ocampo-Martinez et al., 2007], optimal real time control of sewer networks [Marinaki and Papageorgiou, 2005]. Pattern search methods are suitable in this work as the prediction model that is used in the controller. These optimzation methods do not require any explicit information about the gradient of the objective function or constraints to find an optimal solution.

2 SEWER SYSTEMS OPERATION

Sewer systems are drainage networks composed of sewers, collectors, and surface or open channels that drain stormwater and urban sewage. A sewer system is generally composed of one or more catchment areas, the characteristics of which depend strongly on the topography of the area. To manage volumes and flows in the system, several elements are present, such as storage tanks, collectors, valves, and pumping stations. A storage tank is used to store excess rain in order to avoid overflows. In combined sewer systems such overflows are referred to as combined sewer overflows (CSO). A collector is a conduit that receives stormwater and/or sewage from lateral sewers or other branch conduits. Valves are elements that essentially constrain or block the sewer and allow to regulate its flows. A pumping station is a facility including pumps and equipment to push sewage to wastewater treatment plants. It is worth noting that a wastewater treatment plant has a limited capacity (maximum input flow). Under normal conditions, operators or local controllers act on the system with the aim to locally regulate volumes and flows in the network. Under particular conditions such as intense rainfall, volumes and flows grow rapidly, and flooding and combined sewer overflows may occur. An efficient use of storage facilities and pumping stations may prevent or minimize such overflows.

2.1 Bogotá case study

The Bogotá sewer system consists of four main catchments: Torca, Salitre, Fucha and Tunjuelo. Each one is drained by one urban river with the same names as the catchments. The sewer system of Bogotá has been developed into two phases: combined catchments form the oldest part of the network while the more recent part is constituted by separated catchments. A part of Salitre catchment is used for the case study as illustrated by Figure 1 and it includes one treatment plant with a maximum capacity of 4 m^3/s, 3 pumping stations each one composed by a storage tank of minimum capacity and one or several pumps, and 3 storage facilities with regulated output flow. The latter means 6 control inputs. Salitre catchment has been divided in several subsystems (1, 2, 3 in Figure 1) and each one has a local controller that make decisions about actuators' set points. More details about studied subcatchments is depict in table 1.

ID Sub-area	Number of urban sub-catchments (separated sewer system)	Mean Area (Ha)	Mean % Wrong Connections (Sanitary to Pluvial)	Mean % Wrong Connections (Pluvial to Sanitary)	Mean % Residential Use	Mean % Industrial Use	Mean % Comercial Use
1	13	78	13	16	90	5	2
2	18	89	14	22	86	4	7
3	8	63	17	14	91	1	4

Table 1: Detail description about studied subcathments in Bogotá sewer systems, see figure 1.

The main problems related with the combined system in Bogotá can be summarized as follows: direct discharges

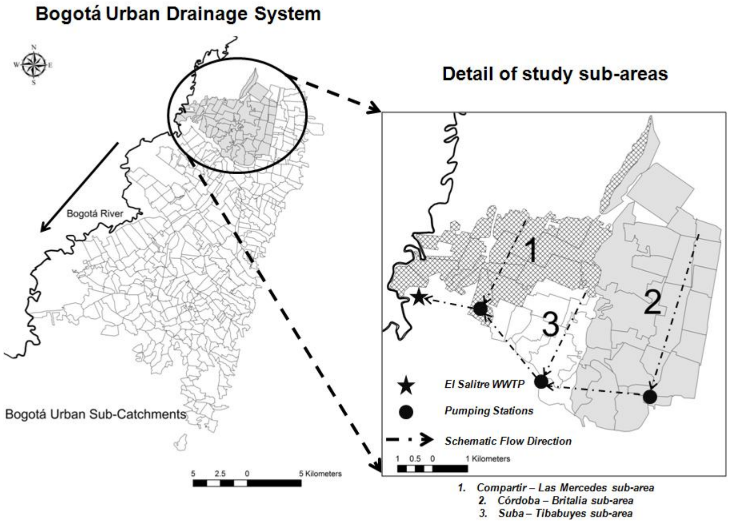


Figure 1: Bogotá Sewer System - Salitre catchment. Compartir Las Mercedes subcatchment (1), Córdoba Britalia subcatchment (2) and Suba Tibabuyes subcatchment (3).

of wastewater without treatment as a consequence of the absence or lack of adequate infrastructure, and some combined sewer overflows (CSO) discharges even during dry weather periods. Regarding the separate system, there are many wrong connections from the wastewater system flowing into the storm drainage system and viceversa. As a consequence of wrong connections, the water quality in the storm drainage channels is bad and there is a high risk of sanitary sewer flooding during intense rainfall events. Actually, the separate system acts more as a *dual* combined system rather than as a separate one, [GRUCON-IEH-Soprin, 1999]. Clearly the physical limitations in terms of maximum volumes and flows would not permit to completely prevent the overflows in the system, but an improvement in the coordination of the local controller actions of storage tanks and pumping stations could help to reduce the overflows when such strong rainfall events occur. This is the purpose of the control scheme that is proposed in this paper. Therefore stormwater and sewage flows that enter into the system are considered as disturbances. In a recently published paper ([Leirens et al., 2010]), the stormwater and sewage profiles used did not vary between sub-catchments, i.e. a single profile of stormwater and a single profile of sewage were used to simulate the system. For this work it is worth noting that one profile of rain and one profile of sewage were used for each sub-catchment, which means that the model is able to take into account the spatial and temporal variability of stormwater and the generation of sewage. These profiles have been calculated and validated with measurements taken between 2006 and 2009 by the environmental engineering research centre (CIIA from its Spanish name - Centro de Investigación en Ingeniería Ambiental) at Universidad de los Andes. The Bogotá urban drainage model uses a seven-step parsimonious methodology in order to generate a set of stochastically-defined dry weather profiles (DWF) profiles for each non-measured subcatchment and each state variable (such as wastewater flow, Biochemical Oxygen Demand - BOD -, Chemical Oxygen Demand - COD - Total Suspended Solids - TSS -, among others). The proposed methodology is supported by data collected from field campaigns and the subcatchment's well-known properties (such as land use, per-use consumption distribution, area, slope, travel time, etc.); all these taking into account the profile's inherent uncertainty.

2.2 Integrated Bogotá sewer system modeling

Research groups in Bogotá have been working in co-operation with the sewer system managers with the final aim of increasing understanding of the interactions between the sewer system, the wastewater treatment system and the receiving water system. As part of this, a software tool - named *City Drain*© - is being used, customized and implemented for Bogotá city. This open source toolbox was developed by [Achleitner et al., 2007] for integrated urban drainage modelling based on the European Water Framework Directive (WFD) requirements. The *City Drain*© toolbox has been developed within $Matlab/Simulink$©. The key aspect of using this modelling environment (which is actually used in several integrated simulators) is that the user can choose and freely adapt from a block library representing the elements of the total system. Overall the computation is based on a fixed discrete time step approach where each subsystem uses the same time increments, usually being predetermined by the temporal resolution of the rain data used. For allowing long term simulations the blocks implemented are based on simple conceptual models for hydraulics (frequently denoted as hydrological models i.e., Muskingum model [Achleitner et al., 2007]). The toolbox provides 5 different types of blocks in order to build an integrated urban drainage model, they are: the source blocks, the catchment and sewer blocks, the wastewater treatment plant blocks, the river blocks and some tool blocks. The source blocks include Flow-read (reads flow data such as time, flow and concentrations from ASCII files), Rain-read (reads rain data from ASCII files having a predefined format), Rain-generator (generates rain data by means of a simple stochastic algorithm), QCM-Generator (generates a dynamic output on a weekly basis either for flow, concentration or mass). The catchment blocks include different blocks for representing combined and separate sewer systems on a catchment level. Stormwater runoff is modelled here by means of a catchment loss model (which accounts for initial and permanent losses) coupled with a simplified Muskingum routing method, having as inputs rain volume per time step, dynamic dry weather flow, dynamic infiltration flow and wastewater/stormwater flow introduced from an upstream catchment. There are two different conceptual approaches to integrated modelling: sequential and parallel. The City Drain toolbox can be classified as parallel one. Compared with sequential modelling, parallel modelling offers major advantages when a feedback is necessary (e.g., for real time control - RTC - applications). This is possible because all the components of the urban drainage system are simulated simultaneously. For example with a parallel simulation, the current and predicted states of the river water can be used to determine the control actions in the sewer system, whereas in sequential simulation this is not possible, since the water quality is only calculated after the simulation of the other system is completed. Special blocks, named retention catchment blocks, which allow for conceptually representing backpressure effects are provided. The sewer blocks (with and without retention as well) allow for flow/pollutant routing in a sewer using the Muskingum routing method [Achleitner et al., 2007]. Other provided blocks are CSO structures, wrong connections, pumping stations and WWTP. The river blocks also use the Muskingum method for flow routing. Different blocks offer the possibility to simulate single or multiple stretches and to include pollutant transport or not. [Rodríguez et al., 2008] and [Díaz-Granados et al., 2009] presented the development of an integrated modelling approach for the Bogotá urban drainage system (model set-up). This includes an overview of the older, recent and ongoing research towards improved management of urban drainage systems using an integrated framework.

3 PREDICTIVE CONTROL OF SEWER SYSTEMS

In model predictive control, the control actions are obtained at each control sample step k_c by solving an optimization problem that minimizes an objective function over a finite prediction horizon, subject to the evolution of the prediction model specified by the mapping $\mathcal{P}$ and operational constraints, e.g., on control inputs [Maciejowski, 2002]. The objectives considered, cost function and constraints for the case study are the following:

- Ensure the use at its full hydraulic capacity of treatment of the wastewater treatment plant, while minimizing overflows that occur when the sum of the pump flows is larger than the maximum capacity of the treatment plant.
- Reduce or avoid overflows of the sub-catchments (storage tanks) of the sewer system.
- Minimize the economic cost when using the pumping stations since they can be used before rainfalls and/or after it has stopped falling.

The bounds on the control inputs $\mathbf{u}$, e.g., minimum and maximum thresholds $v_\mathrm{pump}^\mathrm{min}$ and $v_\mathrm{pump}^\mathrm{max}$ for the local controller of the pumps, and minimum and maximum output flow rates $q_\mathrm{out}^\mathrm{min}$ and $q_\mathrm{out}^\mathrm{max}$ of the storage tanks, are taken into account in the form of inequality constraints:

$$\mathbf{u}_\mathrm{lower} \leq \mathbf{u}(k_\mathrm{c} + i) \leq \mathbf{u}_\mathrm{upper}, \tag{1}$$

for $i \in \{0, \ldots, N_\mathrm{c} - 1\}$.

The combined control objectives give us the cost function over the prediction horizon defined as:

$$J\big(\tilde{\mathbf{u}}(k_\mathrm{c}), \tilde{\mathbf{y}}(k_\mathrm{p})\big) = \sum_{i=0}^{N_\mathrm{p}} \Big(J_\mathrm{TP}\big(\mathbf{y}(k_\mathrm{p}+i)\big) + \ J_\mathrm{overflow}\big(\mathbf{y}(k_\mathrm{p}+i)\big) + J_\mathrm{pump}\big(\mathbf{y}(k_\mathrm{p}+i)\big)\Big). \tag{2}$$

There is a weight factor for each objective and their values has beeen determined of appropriate dimensions. For example, the J_pump factor mantain its value because the cost of operation of a pump is considered contant. In J_TP

and J_{overflow} cases, their weight values are changing because of the priority of the system at the time instant i.e., when a storwater is present the main objective is to avoid the overflows in storage tanks so the weight factor must be major than J_{TP}. The event when there is dry weather present, the priority is to treat the major quantity of water in the waste water treatment plant so J_{TP} will major than J_{overflow}.

3.1 MPC optimization problem

The MPC problem can now be formulated as an optimization problem that has to be solved at each control step, given current states $\mathbf{x}_{\text{c}}(t_0)$, $\mathbf{x}_{\text{d}}(t_0)$, and $\mathbf{u}(k_{\text{c}}-1)$ at t_0:

$$\min_{\tilde{\mathbf{u}}(k),\tilde{\mathbf{y}}(k)} J\big(\tilde{\mathbf{u}}(k),\tilde{\mathbf{y}}(k)\big) \tag{3}$$

subject to

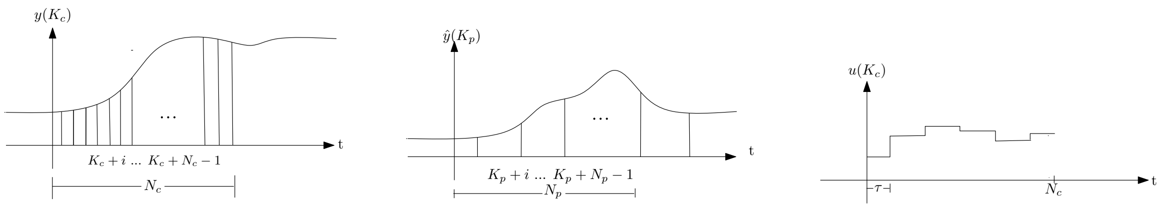
$$\tilde{\mathbf{y}}(k) = \mathcal{P}\big(\mathbf{x}(k),\tilde{\mathbf{u}}_{\text{c}}(k)\big) \tag{4}$$

$$\tilde{\mathbf{u}}_{\text{lower}} \leq \tilde{\mathbf{u}}(k) \leq \tilde{\mathbf{u}}_{\text{upper}} \tag{5}$$

$$\tilde{\mathbf{y}}_{\text{lower}} \leq \tilde{\mathbf{y}}(k) \leq \tilde{\mathbf{y}}_{\text{upper}} \tag{6}$$

Where $\mathcal{P}$ maps the initial continuous state. By substituting the prediction model (4) into the objective function (3) an optimization problem with a nonlinear, non-differentiable objective function and simple box constraints is obtained. More details on the mathematics of predictive control, objectives and constraints for the case study can be found in [Leirens et al., 2010].

Figure (2) depicts the MPC strategy. Future outputs for a determined prediction horizon N_p are predicted at each instant using the model. These predicted outputs $\hat{y}(K_p)$ depend on the known values up to instant $K_c + i$ and on the control signals $u(K_c - 1)$, which are computed to be sent to the system. The set of future control signals is calculated by optimizing a determined criterion to keep the system as close as possible to the reference trajectory. This criterion usually takes the form of a quadratic function of the errors between the predicted output signal and the predicted reference trajectory. When the model is nonlinear and there are some constraints, an iterative optimization method has to be used to obtain an explicit solution. The control signal $u(K_c)$ is sent to the process whilst the next control signals are rejected, because at the next sampling instant $y(K_c + 1)$ is already known and the procedure can start over again. The operation is repeated with this new value and all the sequences are brought up to date. Thus, the $u(K_c + 1)$ is calculated using the receding horizon concept. τ represents the time that the optimizer takes to compute the new control signals.



(a) Process output (b) Predictor output (c) Control input

Figure 2: MPC strategy.

3.2 Prediction model

This section details how the City Drain toolbox model can be used as a prediction model. Consider a time interval $[t_0, t_f]$, i.e., the prediction interval. Given an initial continuous state $\mathbf{x}_{\text{c}}(t_0) \in \mathbb{R}^{n_{x_{\text{c}}}}$, an initial discrete state $\mathbf{x}_{\text{d}}(t_0) \in \mathbb{R}^{n_{x_{\text{d}}}}$, and a collection of inputs $\mathbf{u}(t) \in \mathbb{R}^{n_u}$ over the full prediction interval, computing a prediction means solving an initial value problem and obtaining the outputs $\mathbf{y}(t) \in \mathbb{R}^{n_y}$, for $t \in [t_0, t_{\text{f}}]$. In a discrete-time control framework, control inputs are provided at discrete control sample steps $k_{\text{c}} + i$, for $i = \{0, 1, \dots\}$, where $k_{\text{c}} + i$ corresponds to continuous time $t_0 + (k_{\text{c}} + i)T_{\text{c}}$ and T_{c} is the control sample time. A zero-order hold is used to maintain the control inputs constant between two control sample times, i.e., $\mathbf{u}(t) = \mathbf{u}(k_{\text{c}})$ for $t \in [t_0 + k_{\text{c}}T_{\text{c}}, t_0 + (k_{\text{c}} + 1)T_{\text{c}})$. Then a prediction model is given by a sequence of N_{c} inputs, $\tilde{\mathbf{u}}(k_{\text{c}}) = \big[\mathbf{u}^{\text{T}}(k_{\text{c}}), \dots, \mathbf{u}^{\text{T}}(k_{\text{c}} + N_{\text{c}} - 1)\big]^{\text{T}}$, where $N_{\text{c}} = \lfloor \frac{t_{\text{f}} - t_0}{T_{\text{c}}} \rfloor + 1$ is the number of control inputs over the prediction horizon ($\lfloor \tau \rfloor$ is the integer part of τ). Similarly, we assume that computing the output $\mathbf{y}$ for every T_p time units adequately represents the underlying continuous signals. The output sequence is then defined as $\tilde{\mathbf{y}}(k_\mathrm{p}) = \left[\mathbf{y}^\mathrm{T}(k_\mathrm{p}), \ldots, \mathbf{y}^\mathrm{T}(k_\mathrm{p}+N_\mathrm{p}-1)\right]^\mathrm{T}$, where $N_\mathrm{p} = \lfloor \frac{t_\mathrm{f}-t_0}{T_\mathrm{p}} \rfloor + 1$. For the Bogotá case study, the sewer system model built with the City Drain toolbox does not contain algebraic loops nor implicit differential equations, and therefore without loss of generality, we can assume that the prediction model is given by the mapping

$$\tilde{\mathbf{y}}(k_\mathrm{p}) = \mathcal{P}\left(\mathbf{x}_\mathrm{c}(t_0), \mathbf{x}_\mathrm{d}(t_0), \tilde{\mathbf{u}}(k_\mathrm{c})\right), \tag{7}$$

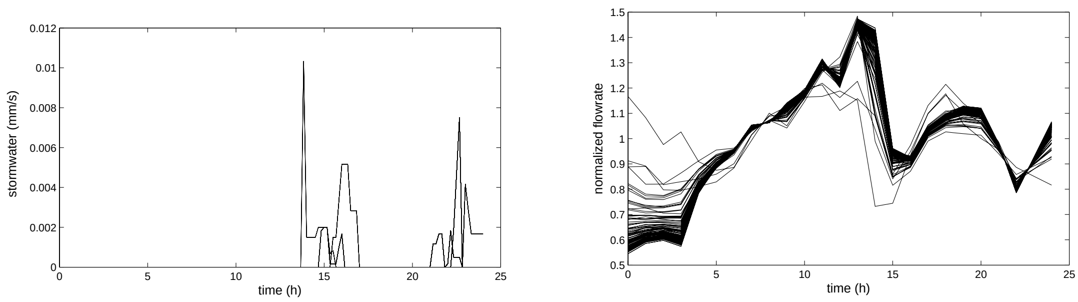
where $\mathcal{P}$ maps the initial continuous state $\mathbf{x}_\mathrm{c}(t_0)$ and discrete state $\mathbf{x}_\mathrm{d}(t_0)$ at time t_0, and the N_c inputs collected in $\tilde{\mathbf{u}}(k_\mathrm{c})$ to the N_p outputs collected in $\tilde{\mathbf{y}}(k_\mathrm{p})$. The prediction model $\mathcal{P}$ involves continuous-time dynamics in the form of nonlinear differential equations in combination with discrete-event dynamics in the form of discrete logic and if-then-else rules. Therefore, the sewer system model is a nonlinear and nonsmooth dynamical system and consequently, computing numerical solutions, i.e., predictions, is a costly process. It's worth to note that although both models are the same (process and simulator) the sample time used for both cases is different i.e., $T_c < T_p$ where T_c is the sample time at process simulation and T_p is the sample time at prediction stage.

4 Pattern-search methods for nonlinear optimization

In the MPC problem defined above (after the substitution of the prediction model) evaluating the objective function is expensive due to the evaluation of the prediction model which involves a Simulink simulation. In practice, computation time is limited and within the available computation time a solution that is as good as possible has to be determined. Solvers that use this first-order or second-order information will therefore perform numerical estimation, involving numerous objective function evaluations. In addition, due to the non-smoothness of the problem there are many local minima in which this type of solvers typically can get stuck quickly. We propose to use a so-called direct-search optimization method, which does not explicitly require gradient and Hessian information [Wright, 1996]. The only property that this method requires is that the values of the objective function can be ranked. This feature together with the feature that direct-search methods are suitable for non-smooth problems, make that such a method is suitable for solving the control problem at hand. In particular, we propose to use the direct-search method pattern-search [Lewis et al., 2000] for its straightforward implementation and its ability to yield good solutions, even for objective functions with many local minima. For a more detailed description about this optimization method see [Dennis and Torczon, 1994] and for its application see [Leirens et al., 2010].

5 Simulation results, conclusions and future work

Several different events had been studied for the Bogotá case study and one of the simulated events which good results are presented in this section. The City Drain model is used both for representing the system to be controlled and as a prediction model in the model predictive controller. Typically, rainfall and sewage predictions until 5 h ahead are considered accurate. The average settling-time of the system is around 1 h. Consequently, the prediction step T_p is selected equal to 1 h and the control step T_c is selected equal to 10 mins. The prediction horizon is 5 h, i.e., N_p = N_c = 5 and the simulation time is 24 h, starting at midnight.

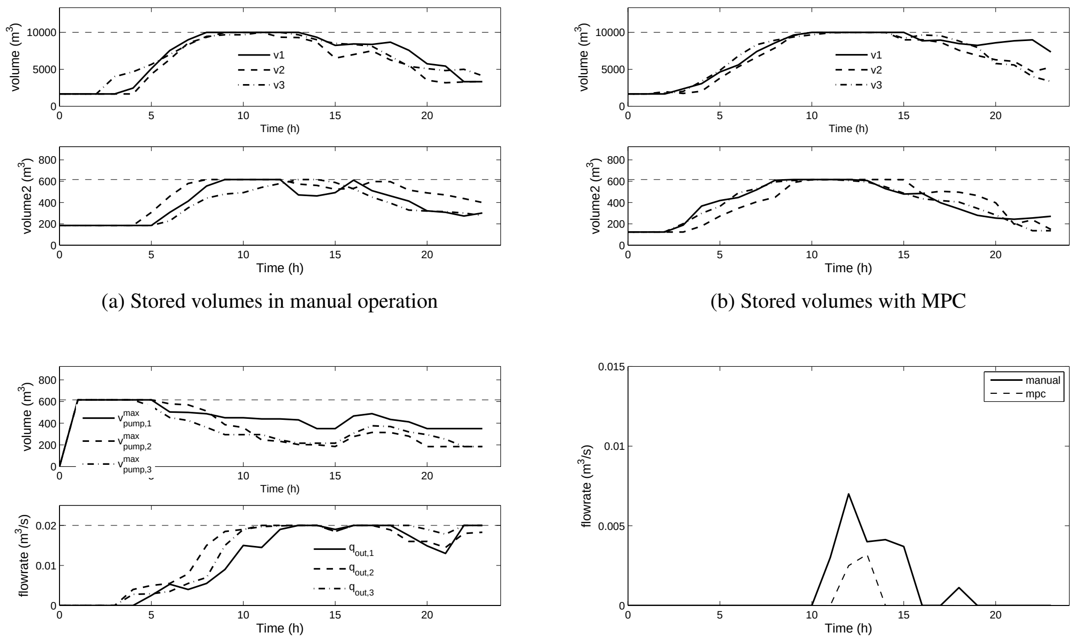


(a) Stormwater profiles

(b) Normalized sewage profiles

Figure 3: Disturbances profiles.

In this simulation case several sewage profiles are used. Each profile is generated in a stochastic way and is associated to each subcatchment of the system. The generation of the profiles (figure 3) has been calibrated and validated by the CIIA. In figure 3b a spatial variation in profiles can be seen, the latter caused by the differences in the land use of the subcatchment (i.e., industrial, domestic). In manual operation mode, actuators of the system (3 storage tanks and 3 pumping stations) do not change their values of input control. For this case outputs flow of storage facilities are completely open, while the set piont to start pumps of pumping stations is setted at almost the maximum capacity of storage of tanks of pumping stations. The latter means that pumps are started only when is necessary. Storage facilities are used in both cases (manual and MPC). Figures (4c) and (4d) depicts the evolution of the accumulated volumes in storage tanks (volume) and in tanks of pumping stations (volume2). A more efficient use of storage facilities is presented in figure (4b). In figure (4b) accumulated volumes are greater than accumulated volumes in figure (4a), because with the MPC, storage facilities help to not violate the constraint of maximum capacity of the treatment plant.



(a) Stored volumes in manual operation

(b) Stored volumes with MPC

(c) Control inputs for storage tanks and pumping stations

(d) Overflows are reduced when MPC system is available

Figure 4: System's responses in manual operation (a) and with MPC (b). Control inputs (c) and overflows in system (d).

Figure (4c) shows the maximum thresholds v_{max}^{pump} of the local controller of the 3 pumps and the output flow rates q_{out} of the storage tanks with respect to time, as well as the corresponding bounds. The MPC improves the operation of the sewer system regarding the storage facilities and pumping station operation. The latter can be confirmed by figure (4d), where a comparison of overflows in manual operation (that occurs in storage facilities) with overflows with MPC is made. For others studied events, depending of the stormwater intensity, the accumulated volumes at storage facilities are reduced and the improvement performance of sewer system is reduced (CSO minimized). The MPC controller uses an internal model of the system to predict its future behavior and to choose the best actions to apply to minimize the consequences of strong rainfall events, i.e., overflows, and to improve the operation. The prediction model has been built with the City Drain toolbox. The prediction model is non differentiable and a pattern-search algorithm is used to solve the optimization problem that arises from the MPC strategy. The results show the capabilities of the proposed approach applied to the operation of the Bogotá sewer system. The use of a simulator as a predictor model supports this application for sewer systems that are modeled in City Drain. The required time to compute the whole information and to obtain results is compatible with real-time operation in the Bogotá network. Future research will focus on further assessing the performance of the proposed scheme in particular taking into account practical time constraints. Moreover, robustness of the scheme will also be investigated by explicitly considering uncertainty in the disturbance profiles. Furthermore, distributed implementations of the scheme will be considered in a distributed MPC setup in which the different parts of the city will have dedicated MPC which controllers, which via coordination locally choose actions that are system-wide optimal.

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