Application of Predictive Control Strategies to the Management of Complex Networks in the Urban Water Cycle

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The management of the urban water cycle (UWC) is a subject of increasing interest because of its social, economic, and environmental impact. The most important issues include the sustainable use of limited resources and the reliability of service to consumers with adequate quality and pressure levels, as well as the urban drainage management to prevent flooding and polluting discharges to the environment.

Climate change is expected to produce regional changes in water availability in the 21st century. For example, Northern and Southern Europe are expected to experience, respectively, an increase and a decrease in mean precipitation, as well as an increase in the magnitude and frequency of extreme events [1]. These changes will have direct consequences through impacts on the availability and quality of water in the water cycle. Optimal management strategies for the systems in the water cycle can contribute to reduce the vulnerability of urban water systems (UWS) to climatic variability and change.

A UWC is mainly comprised of the following systems:

1) supply/production: water supply from superficial or underground sources and treatment to achieve necessary quality levels
2) transport networks, which use natural or artificial open-flow channels and/or pressurized conduits to deliver water from the treatment plants to the consumer areas
3) water distribution to consumers, involving pressurized pipeline networks, storage tanks, booster pumps, and pressure/flow control valves
4) urban drainage and sewer systems carrying waste and rain water together to wastewater treatment plants (WWTP) before returning it to the receiving environment.

In urban environments, drinking water is provided by means of a drinking water network (DWN) to consumers and industry, and sanitation/urban drainage is achieved through a sewer network (SN). In a large number of cities, DWNs are managed using telemetry and telecontrol systems which provide, in real time, pressure, flow, quality, and other measurements at several key locations within the network. Flow, pressure, and storage control elements are operated from a central dispatch in a centralized or decentralized scheme.

In some cases, advanced urban drainage systems also include a sewage control infrastructure, such as detention tanks, pumps, gates, and weirs. All these elements are monitored and controlled using telemetry/telecontrol systems, which involve rain-gauge networks, wastewater level, and/or flow meters in the sewers and actuators at the valves, pumps, and weirs, a communication network, and monitory and control software. The control system manages the flows and the storage in the network to minimize the risk of untreated water overflows to the streets or to the receiving environment.

The use of optimal control for managing water systems to achieve energy efficiency, cost minimization, and environmental protection is summarized in this article. Applying optimal control concepts to water systems requires the development of control-oriented dynamic models to represent open-channel systems (such as rivers, canals, aqueducts, or SNs), pressurized pipes, or combinations of both, which have nonlinear responses to control actions, such as changing modes at different operating points. Those systems also contain storage and control elements, such as tanks and valves, with a predetermined operational range that leads to the inclusion of physical constraints in the model. Additionally, some on-off elements such as pumps or valves may exist.

The management of the UWS must be carried out predictively. Control actions must be computed ahead of time, with an appropriate time horizon, based on real measurements and on-state estimation, as well as predictions of the stochastic variables involved in the models such as consumer demands in drinking water systems or rain intensities in urban drainage systems. For water distribution networks, the prediction horizon is usually of 24 h. Longer horizons are chosen for water supply and treatment management. For real-time control of urban drainage systems, the horizons depend on the average sewage transport time between the discharge points and the final collection/treatment/discharge points. Thus, the length of those horizons are particular for each application, mainly depending on topographic and physical characteristics of the terrain and the sewers. Predictive and optimal control techniques are a smart option to compute control strategies for

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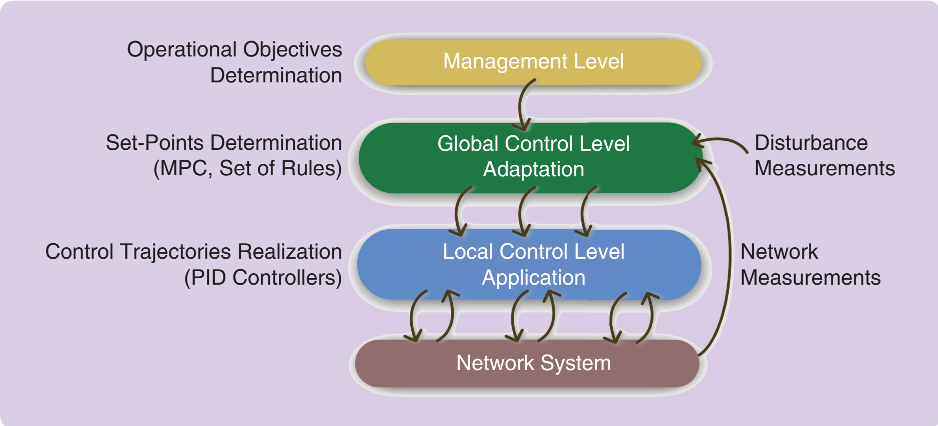

FIGURE 1 Hierarchical structure for the RTC system adapted from [46] and [7]. Here, the MPC, as the global control law, determines the references (set points) for the local controllers placed at different elements of the networked system. These references are computed according to measurements taken from sensors distributed around the network. The management level provides the MPC with its operational objectives that are reflected in the controller design as the performance indices to be enhanced that can be either minimized or maximized. Finally, water systems control requires the use of a supervisory system to monitor the performance of the different control elements in the networks (sensors and actuators) and to take appropriate correcting actions in the case where a malfunction is detected to achieve a proper fault-tolerant control [47].

these complex dynamic systems. To achieve certain control goals, one or more optimization problems are posed using a cost function to represent control goals and a set of constraints to take into account the system dynamics and physical and operating limits. Predictive and optimal control techniques also allow the user to establish priorities among the different control objectives, whenever these cannot be achieved simultaneously [2].

Over the past few years, model predictive control (MPC) has proven to be one of the most effective and accepted control strategies for large-scale complex systems [3], [4]. The objective of using this technique for controlling UWS is to compute, in a predictive way, the manipulated inputs to achieve the optimal performance of the network according to a given set of control objectives and predefined performance indices. As shown in [5]–[8], such controllers are suitable to be used in the global/supervisory control of networks related to the UWC. Figure 1 shows a conceptual scheme for a hierarchical structure considered on the control of networks related to the UWC.

This article summarizes the real-time global optimal management of two systems of the UWC, both of them located in Barcelona, Spain: its DWN—specifically the transport network—and a representative portion of its SN. Real-time control (RTC) of both types of UWC systems has received special attention during the last few years, due to the increasing demand for improved system performance to meet consumer and regulatory needs, often at reduced cost [5], [9]. The main goal to be achieved in DWNs is to reduce pumping costs—for instance, by filling tanks in low tariff periods—while maintaining adequate system pressure to meet fluctuating consumer demands [10]. Similarly, in urban drainage management, the goals are to minimize flooding and combined sewer overflow (CSO) to the receiving environment by controlling flow within the wastewater system, through, for example, in-line storage [11] or using underground detention tanks, gates, and pumps [6], [12].

CONTROL-ORIENTED MODELING PRINCIPLES

Complex nonlinear models are very useful for off-line operations (for instance, calibration and simulation). Detailed mathematical representations such as the Saint-Venant equations for describing the open-flow behavior in SNs [13] or pressure-flow models for DWNs allow the simulation of those systems with enough accuracy to observe specific phenomena, which is useful for design and investment planning. However, for on-line computation purposes such as those related to global management, a simpler and control-oriented model structure must be conveniently selected. This simplified model includes the following features:

1) representativeness of the main network dynamics: must provide an evaluation of the main representative hydrological/hydraulic variables of the network and their response to control actions at the actuators
2) simplicity, expandability, flexibility, and speed: must use the simplest approach capable of achieving the given purposes, allowing very easily to expand, and/or modify the modeled portion of the network
3) amenability to on-line calibration and optimization: this modeling approach must be easily calibrated online using data from the telemetry system and embedded in an optimization problem to achieve the network management objectives.

This section deals with the control-oriented model principles for the DWN and SN systems described in this article. The distinction is done at the stage of component description while the structure of the model from the merging of elements is described and discussed in a unified way for both systems, determining then the correspondence of their variables with the common variables established in the control theory.

Drinking Water Networks

Several modeling techniques dealing with DWNs have been presented in the literature (see, e.g., [14], [13]). Here, a control-oriented modeling approach that considers a flow model is outlined that follows the principles presented by the authors in [5], [6], and [15]. The extension to include the pressure model can be found in [14], [13], and [16]. A DWN generally contains a set of pressurized pipes, water tanks at different elevations, and a number of pumping stations and valves to manage water flows, pressure, and elevation to supply water to consumers.

The DWN model can be considered as composed of a set of constitutive elements, which are presented and discussed below. Figure 2 shows, in a small example, the interconnection of typical constitutive elements.

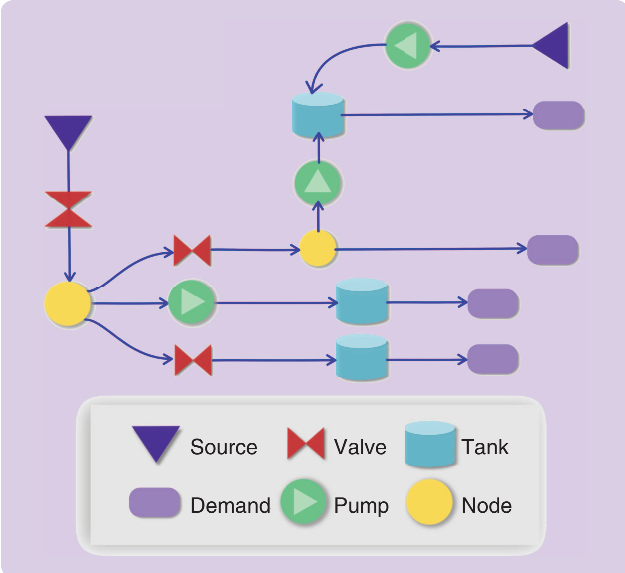

FIGURE 2 Example of a basic topology of a generic drinking water transport network. The interaction of the main constitutive elements involve sources that supply water to the system by means of pumps or valves, depending of the nature of the particular source (superficial or underground). Water is moved using manipulated actuators to fill detention tanks and/or supply water to demand sectors.

Tanks

Water tanks provide the entire DWN with the storage capacity of drinking water at appropriate elevation levels to ensure adequate water pressure service to consumers. The mass balance expression relating the stored volume v in the nth tank can be written as the discrete-time difference equation

$$v_n(k+1) = v_n(k) + \Delta t\Big(\sum_j q_{\mathrm{in}}^{jn}(k) - \sum_h q_{\mathrm{out}}^{nh}(k)\Big), \qquad (1)$$

where $q_{\mathrm{in}}^{jn}(k)$ denotes the manipulated inflows from the jth element to the nth tank, and $q_{\mathrm{out}}^{nh}(k)$ denotes the manipulated outflows from the nth tank to the hth element (which includes the demand flows as outflows). Moreover, Δt corresponds with the sampling time and k the discrete-time instant. The physical constraint related to the range of admissible storage volume in the nth tank is expressed as

$$\underline{v}_n \le v_n(k) \le \overline{v}_n, \quad \text{for all } k, \qquad (2)$$

where $\underline{v}_n$ and $\overline{v}_n$ denote the minimum and the maximum admissible storage capacity, respectively. Notice that $\underline{v}_n$ might correspond with an empty tank; in practice, this value can be set as nonzero to maintain an emergency stored volume.

For simplicity, the dynamic behavior of these elements is described as a function of volume. However, in most cases the measured variable is the tank water level (by using level sensors), which implies the computation of volume taking into account the tank geometry.

Actuators

Two types of control actuators are considered: valves and pumps, or more precisely, complex pumping stations. A pumping station generally contains a number of individual pumps with fixed of variable speed. In practice, it is assumed that the flow through a pumping station is a continuous variable in a range of feasible values. The manipulated flows through the actuators represent the manipulated variables, denoted as q_u. Both pumping stations and valves have lower and upper physical limits, which are taken into account as system constraints. As in (2), they are expressed as

$$\underline{q_u}_m \leq q_{u_m}(k) \leq \overline{q_u}_m, \quad \text{for all } k, \tag{3}$$

where $\underline{q_u}_m$ and $\overline{q_u}_m$ denote the minimum and the maximum flow capacity of the mth actuator, respectively. Since this modeling is stated within a supervisory control framework, it is assumed that a local controller is available, which ensures that the required flow through the actuator is obtained.

Nodes

These elements correspond to the network points where water flows are merged or split. Thus, nodes represent mass balance relations, modeled as equality constraints related to inflows—from other tanks through valves or pumps—and outflows, the latter being not only manipulated flows but also demand flows. The expression of the mass balance in these elements can be written as

$$\sum_j q_{\text{in}}^{jr}(k) = \sum_h q_{\text{out}}^{rh}(k), \tag{4}$$

where $q_{\text{in}}^{jr}(k)$ denotes inflows from the jth element to the rth node, and $q_{\text{out}}^{rh}(k)$ denotes outflows from the rth node to the hth element. From now on, node inflows and outflows will be denoted by q_{in} and q_{out}, even if they are manipulated variables (denoted by q_u).

Demand Sectors

A demand sector represents the water demand of the network users of a certain physical area. It is considered as a measured disturbance of the system at a given time instant. The demand can be anticipated by forecasting algorithms, which are integrated within the MPC closed-loop architecture. For the cases of study in this article, the algorithm proposed in [17] is considered. This algorithm typically uses a two-level scheme composed of

1) a time-series model to represent the daily aggregate flow values
2) a set of different daily flow demand patterns according to the day type to cater for different consumption during the weekends and holidays periods. Every pattern consists of 24-hr values for each daily pattern.

The algorithm runs in parallel with the MPC algorithm. The daily series of hourly flow predictions are computed as a product of the daily aggregate flow value and the appropriate hourly demand pattern. Regarding the daily demand forecast, its corresponding flow model is built on the basis of an autoregressive integrated moving average time-series modeling approach described elsewhere [18]. Then, the structure of the daily flow model for each demand sensor may be written as

$$\begin{aligned} y_p(k) = &-b_1 y(k-1) - b_2 y(k-2) - b_3 y(k-3) - b_4 y(k-4) \\ &-b_5 y(k-5) - b_6 y(k-6) - b_7 y(k-7), \end{aligned} \tag{5}$$

where the parameters $b_1, \ldots, b_7$ are estimated based on historical data. The 1-hr flow model is based on distributing the daily flow prediction provided by the time-series model in (5) using an hourly flow pattern that takes into account the daily/monthly variation as

$$y_{ph}(k+i) = \frac{y_{\text{pat}}(k,i)}{\sum_{j=1}^{24} y_{\text{pat}}(k,i)} y_p(k), \qquad i = 1, \ldots, 24, \tag{6}$$

where $y_p(k)$ is the predicted flow for the current day k using (5), and $y_{pat}(k)$ is the prediction provided by the flow pattern with the flow pattern class day/month of the current day. Demand patterns are obtained from statistical analysis.

Sewer Networks

Sewers are open canals. The Saint-Venant equations, based on physical principles of mass conservation and energy, allow the accurate description of the open-canal flow in sewer pipes [13] and, therefore, also allow a detailed nonlinear description of the system behavior. These partial-differential equations constitute a nonlinear system that is, in general, solved by iterative numerical procedures. For an arbitrary geometry of the sewer pipe, these equations may not have an analytic solution. Notice that these equations describe the system behavior in high detail. However, this level of detail is not useful for real-time implementation in an optimal control scheme due to the high computational cost of obtaining the solution.

Several simplified modeling techniques that deal with the RTC of SNs have been presented in the literature (see, e.g., [19]–[21], [7]). The modeling approaches presented here follow closely the mathematical modeling principles given in [22]. The sewage system is divided into a set of catchments, each one conceptually represented as a virtual tank, as described in [22] and [23] (see also "Virtual Tank Concept").

Using the virtual tank modeling principle and the mass balance conservation law, an SN can be decomposed in a set of catchments described by using the elementary models explained below, shown in Figures 3 and 4, to obtain a simpler

Virtual Tank Concept

At any given time, let the virtual tank be a storing element that represents the total volume of sewage inside the sewer mains associated with a determined subcatchment of a given SN. The sewage volume is computed through the mass balance of the stored volume, the inflows and outflows related to the sewage mains, and the equivalent inflow associated with the rain water [22], [23], [12].

network. This representation also includes other sewer infrastructure elements such as detention tanks, gates, and weirs (other common sewage system elements such as pumping stations can be easily represented by using the mentioned modeling principles but are omitted here as they are not taken into account in the SN case study considered in this article). The set of elements is presented below. A conceptual scheme is included to describe its operation and also for explaining the mathematical relations and derived equations.

Virtual and Real Tanks

Consider that an SN is composed by n tanks, from which n_1 tanks are virtual and n_2 are real, with $n = n_1 + n_2$. In the case of virtual tanks, used to model network catchments, the mass balance equation relates the stored volume, the flows in sewers going into and out of the tanks, and the rain entering the catchment as follows:

$$\begin{aligned} v_{n_1}(k+1) &= v_{n_1}(k) + \Delta t \varphi_{n_1} S_{n_1} P_{n_1}(k) \\ &\quad + \Delta t \left(\sum_j q_{\text{in}}^{n_1 j}(k) - \sum_h q_{\text{out}}^{n_1 h}(k) \right), \end{aligned} \tag{7}$$

where φ_{n_1} corresponds with the ground absorption coefficient of the n_1th catchment, S_{n_1} is the surface area, $P_{n_1}(k)$ is the rain intensity at each sample with a sampling time Δt. The manipulated variables of the system, denoted as $q_{\text{in}}^{n_1 j}$, are the flows through control gates. Tank outflows are assumed to be proportional to the water volume currently stored within the tank, that is,

$$q_{\text{out}}^{n_1 h}(k) = \beta_{n_1} v_{n_1}(k), \tag{8}$$

where β_{n_1} is defined as the volume/flow conversion (VFC) coefficient as suggested in [24] by using the linear tank model approach. This relation can be made more accurate, but more complex, if (8) is considered to be nonlinear (nonlinear tank model approach) or by considering linear models with online parameter estimation [25]. See, for example, [26], where nonlinear models are identified as a function of inflows and outflows.

Limits on the admissible volume of real tanks are expressed as

$$0 \le v_{n_2}(k) \le \overline{v}_{n_2}, \quad \text{for all } k, \tag{9}$$

where $\overline{v}_{n_2}$ denotes the maximum volume capacity. As this constraint is physical, it is impossible to send more water to a real tank than it can store. Notice that real tanks without overflow capability have been considered. Virtual tanks do not have a physical upper limit on their capacity. This fact represents the case when the sewage level in sewers has reached a limit so that overflow situation or flooding to the street occurs. Hence, when the maximum volume $\overline{v}$ is reached in a virtual tank, the excess volume is redirected to another tank/catchment within the network or to a receiving environment. This phenomenon is known as CSO. This situation implies a new flow path coming from the tank, denoted as q_d (referred to as virtual tank overflow), which can be expressed as

$$q_d(k) = \begin{cases} \frac{v(k) - \overline{v}}{\Delta t} & \text{if } v(k) \ge \overline{v} \\ 0 & \text{otherwise.} \end{cases} \tag{10}$$

Thus, outflow of the virtual tank is then limited by its maximum volume capacity as

$$q_{\text{out}}(k) = \begin{cases} \beta \overline{v} & \text{if } v(k) \ge \overline{v} \\ \beta v(k) & \text{otherwise.} \end{cases} \tag{11}$$

Consequently, considering this expression for tank overflow, the difference equation (7) related to virtual tanks becomes

$$\begin{aligned} v_{n_1}(k+1) &= v_{n_1}(k) + \Delta t \varphi_{n_1} S_{n_1} P_{n_1}(k) \\ &\quad + \Delta t \left(\sum_j q_{\text{in}}^{j n_1}(k) - \sum_h q_{\text{out}}^{n_1 h}(k) - q_d(k) \right). \end{aligned} \tag{12}$$

Real *detention tanks* are closed concrete structures used to store water in rain events. For this reason, both tank inflow and outflow are controlled using gates. Similarly, the admissible flows into and out of the tank are related to the current volume stored in the tank. Tank inflow is constrained by the current sewage volume of the real tank, by its maximum capacity, and by tank outflow. Since real tanks are considered with no overflow capabilities, inflow is premanipulated by using a flow diversion gate (explained below), what results in the consideration of this component within the modeling of the real tank. Figure 3 shows conceptual schemes of both the virtual and real tanks considered in this article. To restrict the value of the manipulated flow $q_a^{\star}(k)$ to satisfy the maximum flow condition in the input gate, flow through a link is expressed as

$$\tilde{q}_a(k) = \begin{cases} q_a^{\star}(k) & \text{if } q_a^{\star}(k) \le q_{\text{in}}(k) \\ q_{\text{in}}(k) & \text{otherwise.} \end{cases} \tag{13}$$

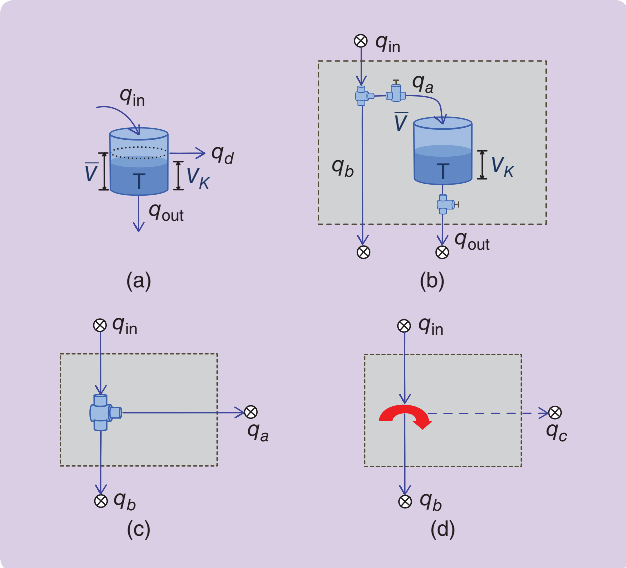

FIGURE 3 Conceptual schemes for SNs constitutive elements. (a) and (b) show the different tanks considered and the common way they are connected and configured (using auxiliary elements according to the case). The elements (a) virtual tank and (b) real tank introduce to the system switching behaviors given when their maximum capacity, namely flow or volume, is achieved. (c) Flow diversion gate. (d) Sewer pipe or weir with single flow.

However, the maximum tank capacity also restricts the inflow according to

$$q_a(k) = \begin{cases} \tilde{q}_a(k) & \text{if } q_b(k) - q_{\text{out}}(k) \le \dfrac{\bar{v} - v(k)}{\Delta t} \\ \dfrac{\bar{v} - v(k)}{\Delta t} & \text{otherwise.} \end{cases} \tag{14}$$

Finally, the tank outflow is

$$q_{\text{out}}(k) = \begin{cases} q^*_{\text{out}}(k) & \text{if } q^*_{\text{out}}(k) \le \beta v(k) \\ \beta v(k) & \text{otherwise,} \end{cases} \tag{15}$$

taking into account that q^*_{out} is also restricted by the maximum capacity of the outflow link, denoted by $\bar{q}_{\text{out}}(k)$. These expressions lead to a difference equation for real tanks in SNs:

$$v(k+1) = v(k) + \Delta t(q_a(k) - q_{\text{out}}(k)). \tag{16}$$

The flow through q_b corresponds to the mass balance

$$q_b(k) = q_{\text{in}}(k) - q_a(k). \tag{17}$$

Controlled Gates

In SNs, gates are used as flow control devices. Depending on the actions they perform, gates can be classified as flow diversion gates, which are used to divert the sewage flow, and detention gates, which are used to stop flow at a certain point in the network. In a real tank, a detention gate is used to control the outflow. Flow diversion gates, shown in Figure 3(c), divert the flow at a junction, controlling flow from one sewer into others. The mass conservation relation in the element is

$$q_{\text{in}}(k) = \sum_j q_u^j(k), \tag{18}$$

where j is an index over all manipulated gate outflows q_u^j, and q_{in} is the flow arriving the gate.

When this modeling approach is employed, the inherent nonlinear dynamics of the SN are simplified by assuming that only flows are manipulated. The physical limits must be included as constraints on system variables (in this case, on the control inputs). For example, the variable q_u^j can never be larger than the tank discharges resulting from the action of gravity on the current volume of water stored in the tank. This constraint is expressed by the inequality

$$\sum_j q_u^j(k) \le \beta_{n_1} v_{n_1}(k). \tag{19}$$

Usually, the range of actuation is also limited, so the manipulated variable must fulfill

$$\underline{q}_u^j \le q_u^j(k) \le \bar{q}_u^j, \tag{20}$$

where $\underline{q}_u$ denotes the lower limit of the manipulated flow and $\bar{q}_u$ denotes its upper limit.

Nodes, Weirs, and Main Sewer Pipes

These components are passive sewer infrastructure elements. Since the descriptions of their dynamics are relatively close, all of them are presented together in this section. Nodes are points of the network where the sewage can be either propagated or merged. Hence, these elements can be classified as splitting nodes and merging nodes. In the case of a set of h inflows q_j, with $j = 1,2,\dots,h$, the expression for the node outflow is expressed as

$$q_{\text{out}} = \sum_{j=1}^{h} q_j. \tag{21}$$

Weirs are passive flow diversion devices built into sewers to derive excess flow from the main sewer (nominal) to another called a spillway. This spillway leads, in some cases, to an overflow discharge point (to a treatment plant or into the receiving environment). Weirs can be seen as splitting nodes having a maximum capacity in the nominal path.

Main sewer pipes are used as connection devices between network constitutive elements [Figure 3(d)]. The set of expressions valid to represent the behavior of a weir is

$$q_b(k) = \begin{cases} \bar{q}_b & \text{if } q_{\text{in}}(k) > \bar{q}_b \\ q_{\text{in}}(k) & \text{otherwise,} \end{cases} \tag{22a}$$

$$q_c(t) = \begin{cases} q_{\text{in}}(k) - \bar{q}_b & \text{if } q_{\text{in}} > \bar{q}_b \\ 0 & \text{otherwise,} \end{cases} \tag{22b}$$

where $\bar{q}_b$ is the maximum flow through q_b and q_{in} is the inflow.

Control-Oriented Model

Considering the set of compositional elements described above, the control-oriented model can be obtained by joining those elements and their corresponding dynamic descriptions. In a general form, the expression which collects all these dynamics can be written as the mapping

$$x(k+1) = g(x(k), u(k), d(k)), \tag{23}$$

where $x \in X \subseteq R^n$ corresponds to the system states, $u \in U \subseteq R^m$ denotes the system inputs (manipulated variables), and $d \in D \subseteq R^p$ denotes the system disturbances. $g: R^n \times R^m \times R^p \to R^n$ is an arbitrary system state function and $k \in Z_+$.

In the case of DWN, (23) is associated to the set of tank expressions in (1). Hence, a control-oriented discrete-time state-space model can be written as [15]

$$x(k+1) = Ax(k) + Bu(k) + B_p d(k), \tag{24}$$

where x corresponds to the water volumes v of the n tanks, u represents the manipulated flows q_u through the m actuators (pumps and valves), d corresponds with the vector of p water demands (measured disturbances affecting the system), and A, B, and B_p are the system matrices of suitable dimensions. Since the system control-oriented model of a DWN does not collect the static dynamics described by DWN nodes in (4), then (24) can be further rewritten as

$$x(k+1) = Ax(k) + \Gamma \mu(k), \tag{25a}$$

$$[E_u \quad E_d]\, \mu(k) = 0, \tag{25b}$$

where $\Gamma = [B \ B_p]$, $\mu(k) = [u(k)^T \ d(k)^T]^T$, and E_u, E_d are matrices of suitable dimensions. Equation (25a) comes from the mass balance in tanks while (25b) comes from the network nodes. Notice that when all the network flows are manipulated, then A is an identity matrix of suitable dimensions.

The case of SN is more complex. As discussed before, the behavior of some elements depends not only on their own state but also on the state of other elements (for example, weirs). Therefore, although the control-oriented model of the SN can be represented, as in the case of DWNs, by a collection of expressions in (12) and (16), some tank inflows and/or outflows can show discontinuous dynamics. Several approaches have been derived for expressing this control-oriented model. In [27], the mixed logical dynamics (MLD) form

$$x(t+1) = Ax(t) + B_1 u(t) + B_2 \delta(t) + B_3 z(t) + B_4 d(t), \tag{26a}$$

$$E_2 \delta(t) + E_3 z(t) \le E_1 u(t) + E_4 x(t) + E_5 + E_6 d(t), \tag{26b}$$

collects, in a linear form, not only the expressions for all the SN constitutive elements but also the physical and operational constraints of those elements. In (26), x corresponds to the sewage volumes v in the n tanks (real and virtual), u represents the manipulated sewage flows q_u through the m actuators (detention and flow diversion gates), and d corresponds to the p rain measurements (after the proper transformation into flow considering the overall network hydrology). Additionally, variables $\delta \in \{0,1\}$ and $z \in R_+$ are auxiliary variables associated with the MLD form. It has been shown that the form (26) of the SN model is equivalent to other representations such as the piecewise affine form, the linear complementary form, and others [28]. A, B_i (with $i \in \{1, \ldots, 4\}$), and E_j (with $j \in \{1, \ldots, 6\}$) are the system matrices of suitable dimensions (see [12] for further details).

Summarizing, Table 1 collects all variables related to the control-oriented models for DWN and SN, as well as their descriptions.

PREDICTIVE CONTROL APPROACHES

The aim of using MPC techniques for controlling networks related to the UWC is to compute, ahead of time, the input actions to achieve the optimal performance of the network according to a given set of control goals. MPC strategies have some important features to deal with complex systems such as DWNs and SNs, namely the amenability to include disturbance forecasts, physical constraints, and multivariable system dynamics and objectives in a relatively simple way.

This section describes the main ideas of the global control of water networks within the MPC framework.

TABLE 1 Variables of control-oriented models and their descriptions.

Type of Variable	Symbol	DWN Description	SN Description
System states	$v(k)$	Tank volumes	Real/virtual tank volumes
Control inputs	$q_u(k)$	Manipulated flows through valves and pumps	Manipulated flows through detention/diversion gates
Measured disturbances	$d(k)$	Water demand	Rain inflow

The predictive control formulation shares some aspects that both types of water networks have in common. These main aspects are treated in this section.

System Model

An adequate system model is one of the main ingredients in the design process of an MPC scheme. In fact, the control law is related to the mathematical nature of the system model. In this article, this aspect has been discussed in the modeling section. Hence, (25) corresponds to the mathematical model considered here in the design of MPC controllers for DWNs. Regarding SNs, the equivalent piecewise linear model of (26), proposed by [29], has been properly considered.

System Constraints

System constraints are given by the physical nature of the variables involved in the modeling process and by some elements present in those networks (for example, merging and/or splitting nodes). In general, these constraints must not be violated due to mass conservation principles or physical restrictions in real elements. Taking into account the flow-based modeling approach discussed in previous sections, models of both DWNs and SNs consider tanks, links/pipes, and pumps/valves as some of their compositional elements. This fact implies the determination of hard constraints for their physical limits as follows:

1) Tank volumetric capacities, which are the network state variable, are limited by

$$x_i^{\min} \le x_i(k) \le x_i^{\max}, \qquad \text{for all } k, i \in \{1, \dots, n\}, \tag{27}$$

where $x_i^{\min}$ and $x_i^{\max}$ denote the minimum and maximum volume capacity, respectively, given in cubic meters.

2) Flows in actuators and in the interconnection links,

$$u_i^{\min} \le u_i(k) \le u_i^{\max}, \qquad \text{for all } k, i \in \{1, \dots, m\} \quad \text{(manipulated variables)}, \tag{28a}$$

$$q_i^{\min} \le q_i(k) \le q_i^{\max}, \qquad \text{for all } k, i \in \{1, \dots, m_2\} \quad \text{(other links, if any)}, \tag{28b}$$

where $u_i^{\min}$ or $q_i^{\min}$ and $u_i^{\max}$ or $q_i^{\max}$ denote the minimum and maximum flow capacities, respectively, given in m^3/s. Moreover, m_2 corresponds with the number of nonmanipulated links in SNs.

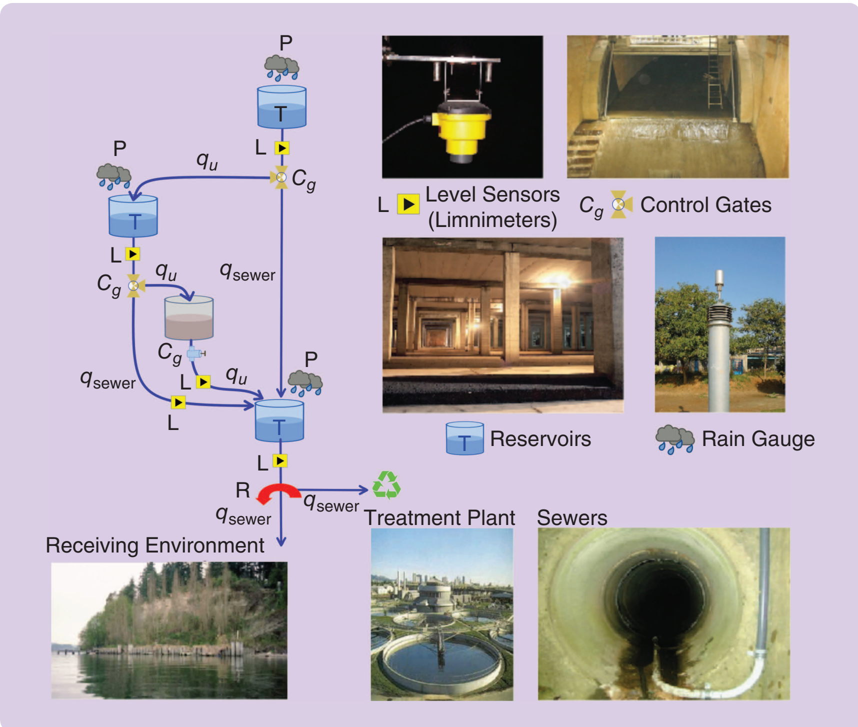

FIGURE 4 Simple SN conformed by some traditional elements. According to the case, there are different types of sensors depending on the measurements taken. Moreover, actuators may be gates or pumping stations; the latter mainly used when storing sewage into multiple-body tanks with complex emptying strategies. Even the WWTPs are in theirself complex systems; their interconnection with the SN allows to determine the way of managing the sewage to avoid pollution phenomena, fulfilling one of the common control objectives for these networked systems.

Control Objectives and Cost Functions

It is possible to use different control objectives for each network of the UWC depending on the operational goals sought by the operators. This section describes the most common control objectives and the resultant multiobjective cost function for each case. Many other criteria can be included by defining the corresponding objective function.

Objectives in DWNs

For DWNs, this article considers and discusses the following control objectives [15], [30].

Minimization of Water Production and Transport Costs

The main economic costs associated with drinking water production are due to treatment processes, water acquisition or use costs, and, most importantly, to electricity costs for pumping. Delivering this drinking water to appropriate pressure levels through the network involves important electricity costs in booster pumping as well as elevation from underground devices. In a specific case, this objective can be mathematically formulated as the minimization of

$$J_1(k) \triangleq (\alpha_1 + \alpha_2(k)) q_u(k), \tag{29}$$

where α_1 corresponds to a known vector related to the economic costs of the water depending on the selected water source, and $\alpha_2(k)$ is a vector of suitable dimensions associated to the economic cost of the flow through certain actuators (pumps only) and their control cost (pumping). Note the k-dependence of α_2 since the pumping cost has different values according to the variable electric tariffs along a day.

Appropriate Management of Safety Water Storage

The satisfaction of water demands must be fulfilled at all times. However, some risk prevention mechanisms need to be introduced in the tank management so that, additionally, the stored volume is preferably maintained above a certain safety value for eventual emergency needs and to guarantee future water availability. This objective may be achieved by minimizing the following expression:

$$J_2(k) = \begin{cases} (v(k) - v^{\text{safe}})^T (v(k) - v^{\text{safe}}) & \text{if } v(t) \leq v^{\text{safe}} \\ 0 & \text{otherwise,} \end{cases} \tag{30}$$

where v^{safe} is a term that determines the safety volume to be considered for the control law computation. This term might appear as unnecessary given the guarantees of the MPC design, but, since a tradeoff between the other costs and the volumes is present, the controller would tend to keep the lowest possible tank water volumes. This fact would reduce the safety of the system to handle unexpected extra demands (such as fire extinction, among others).

Smoothing of Control Action

Valves must also operate smoothly to avoid big transients in the pressurized pipes that could lead to poor pipe condition. The use of a smooth reference change also *helps* the lower-level regulator performance. Similarly, water flows requested from treatment plants must have a smooth profile due to plants operational constraints. To obtain such a smoothing effect, control signal variation between consecutive time intervals is penalized. The penalty term to be minimized is

$$J_3(k) = \Delta q_u(k)^T \, \Delta q_u(k), \tag{31}$$

where $\Delta q_u(k) \triangleq q_u(k) - q_u(k-1)$.

Objectives in SNs

The sewer system control problem has multiple objectives with different priority [7]. According to the literature of SNs, the common control objectives for the management of SNs are briefly discussed below in a given order of decreasing priority.

Minimization of Flooding in Streets

Severe rain, wastewater, and stormwater of the sewer system can saturate the pipes, flowing to the streets. Given that this situation must be avoided, the related objective can be defined as the minimization of the overflows to the street in main sewers and catchments, that is,

$$J_1(k) = \begin{cases} (q(k) - q^f)^T \, (q(k) - q^f) & \text{if } q(k) \geq q^f, \\ 0 & \text{otherwise,} \end{cases} \tag{32}$$

where q^f corresponds with the vector of flooding flows of the involved elements.

Minimization of the CSO to the Receiving Environment

CSO is produced when untreated sewage flows reach a spillway to the receiving environment. This situation must also be avoided, whenever possible. At each time instant the following expression must be minimized:

$$J_2(k) = \begin{cases} (q(k) - q^{\text{pol}})^T \, (q(k) - q^{\text{pol}}) & \text{if } q(k) \geq q^{\text{pol}}, \\ 0 & \text{otherwise,} \end{cases} \tag{33}$$

where q^{pol} is the maximum flow allowed just before releasing sewage to the receiving environment. This term can be seen as a special case of the first objective where only the overflows going to a receiving environment are taken into account. These terms allow a tradeoff between retaining water in the network at the cost of possible flooding in streets, or avoiding that flooding but generating pollution.

Maximization of the Treated Sewage

This objective aims at reducing the amount of untreated sewage that is released to a received environment. This is achieved by minimizing

$$J_3(k) = (q(k) - q^{\text{wwtp}})^T (q(k) - q^{\text{wwtp}}), \tag{34}$$

where q^{wwtp} is the maximum allowed flow into the WWTP. A secondary purpose of this objective consists in trying to empty detention tanks as soon as possible to anticipate future rainstorms. Additionally, this objective indirectly reduces pollution to the environment by means of using, in an optimal way, the storage capacity of the network and, at the same time, the capacity of the treatment plan.

Multiobjective Performance Function

The multiobjective performance function $J(k)$ that gathers the aforementioned control objectives, either in the case of DWN or SN can be written as

$$\mathcal{J}(k) = \sum_{j=1}^{\varphi} \gamma_j J_j(k), \tag{35}$$

where a set of φ control objectives are considered and, in turn, a multiobjective open-loop optimization problem (OOP) is stated. The prioritization of the control objectives is performed by using the order of the mathematical cost function associated to each objective, and also a set of appropriate weights γ_j. These weights are selected offline by means of trial-and-error procedures, taking into account the priority of each objective within the cost function. More sophisticated methodologies for tuning multiobjective control problems based on lexicographic minimizers [2], goal programming [31], or Pareto-front computations [32] may be also considered.

MPC Problem Formulation

Collecting the parts described in previous subsections, the MPC design follows the traditional procedures presented in [33], [34], [3], which involve solving an optimization problem over a prediction horizon H_p, where a cost function is minimized subject to a set of physical and operational constraints. Once the minimization is performed, a vector of H_u control actions over the prediction horizon H_p is obtained. Only the first component of that vector is applied to the plant. The procedure is repeated for the next time instant, taking into account the feedback measurements coming from the system, following the classic receding-horizon strategy.

In general terms, the MPC controller design is based on the solution of an OOP

$$\mathcal{V}(k,H_p) = \min \sum_{i=0}^{H_p} \sum_{j=0}^{\varphi} \gamma_j J_j(k+i|k), \tag{36}$$

subject to the system model and the physical and operational constraints, where the index k represents the current time instant and index i represents the time instant along the future prediction horizon H_p. The notation $k+i|k$ denotes the time instant $k+i$ given k. Notice that (36) corresponds with (35) over the prediction horizon.

The minimum of $\mathcal{V}(k, H_p)$ is achieved by finding a set of optimal variables that generally correspond with the manipulated variables of the system model but could include further variables of a diverse nature. For a prediction window of length H_p and considering $z \in \mathbb{R}^{sH_p}$ as the set of s optimization variables for each time instant over H_p, the multiobjective optimization problem can be formulated as

$$\min_{z \in \mathbb{R}^{sH_p}} f(z) \tag{37a}$$

subject to

$$H_1(z) \leq 0, \tag{37b}$$

$$H_2(z) = 0, \tag{37c}$$

where $f(z)$ comes from the manipulation of (36). The $H_1(z)$ and $H_2(z)$ are vectors of dimensions $r_i H_p \times 1$ and $r_e H_p \times 1$, respectively, containing the constraint functions, where r_i is the number of inequality constraints and r_e is the number of the problem equality constraints. Equations (37b) and (37c) gather all problem constraints including those from the system model, the physical restrictions of its variables, and the operational and management constraints.

Assuming that the OOP (37) is feasible for $z \in \mathbb{R}^{sH_p}$, there exists an optimal solution given by the sequence

$$z^* \triangleq (z^*(0|k), z^*(1|k), \ldots, z^*(H_p|k)). \tag{38}$$

The receding horizon philosophy sets [33]

$$z_{\text{MPC}}(x(k)) \triangleq z^*(0|k) \tag{39}$$

and disregards the computed inputs from $k = 1$ to $k = H_p$, repeating the whole process at the subsequent time step.

The MPC problem formulation in DWNs and SNs gives the expressions for each of the problem parts described above. The mapping (23) must be replaced by the system

Software Tool for MPC Design of DWNs

A general-purpose decision support tool has been developed to allow the user to implement optimal/predictive control techniques in large-scale drinking water systems [16]. The tool has been called PLIO. An important feature of PLIO compared to other existing tools is the application of a unified approach to the complete drinking water system including supplies, production, transport, and distribution and, therefore, pressurized and open-channel dynamics, simultaneously. The modeling and predictive control problem solution algorithm in PLIO is designed for real-time decision support, in connection with a supervisory control and data acquisition system. The hydraulic modeling relies on simple but representative dynamic equations whose parameters are recalibrated online using recursive parameter estimation and real data obtained from sensors in the network. Demand forecast models based on time series analysis are also dynamically updated. The real-time calibration using recursive parameter estimation methods contributes to dealing with hydraulic uncertainty. This modeling choice, as well as the optimization method selection, allows PLIO to deal with very large scale systems. Another distinguishing feature is its capability to accommodate complex operational goals. PLIO was developed jointly by the AGBAR Group and Advanced Control Systems Group (SAC) at the Universitat Politècnica de Catalunya (UPC) and the Spanish National Research Council (CSIC). Currently, PLIO is in the process of becoming a commercial product by Aqualogy AquaAmbiente S.A.

Software Tool for MPC Design of SNs

CORAL is a general-purpose decision support tool that allows the user to apply and implement in real-time predictive optimal control techniques in large-scale urban drainage/sewer systems [38], [16]. The model methodology used by this software tool is described in the modeling section of this article. CORAL has been jointly developed by CLABSA and the Universitat Politècnica de Catalunya (UPC) and has already been tested offline at the Escola Industrial and Riera Blanca test catchments of the Barcelona SN as described in [6] and [25]. The tool was also tested on the Murcia (Spain) network to study the feasibility and potential benefits of the construction of three detention tanks and the use of flow diversion gates. CORAL was developed jointly by the AGBAR Group and Advanced Control Systems Group (SAC) at UPC and the Spanish National Research Council (CSIC). Currently, CORAL is also in the process of becoming a commercial product by Aqualogy Aqua Ambiente S.A.

modeling in (25) or in (26) when treating a DWN or an SN, respectively. The constraints in (37b) and (37c) are conveniently expressed taking into account the type of network and its constitutive components; for example, constraints in (25b) must be included when a DWN is considered. Similarly, constraints in (26b) are taken into account for MPC problems in SNs. In both cases, constraints (2) and (3) are always included. To manage the uncertainty of the system disturbances over the prediction horizon, a suitable approach is the stochastic paradigm, which includes explicit models of uncertainty/disturbances in the design of control laws and by transforming hard constraints into probabilistic constraints. As reviewed in [35], the stochastic approach is classic in the field of optimization; a renewed attention has been given to stochastic programming [36] as a powerful tool for robust control design, leading to stochastic MPC and specially to chance-constrained MPC (CC-MPC) [37].

APPLICATION RESULTS: BARCELONA (SPAIN) NETWORKS

In this section, some relevant results obtained from the MPC application to the global control of real water network systems in Barcelona (Spain) are presented and briefly discussed. The case studies have been implemented using two software tools developed jointly by the authors' team and the AGBAR and CLABSA companies in Barcelona. These tools are CORAL (for SNs), which is described in [38] "Software Tool for MPC Design of DWNs," and "Software Tool for MPC Design of SNs," and PLIO (for DWNs), described in [16] and [25].

The optimization method used by the software tools to solve the resulting optimization problems (37) is a generalized reduced gradient search, first suggested in [39], implemented in the CONOPT solver as part of the GAMS library, which can cater for the nonlinear performance index and constraints. The software starts by finding a feasible solution; then, an iterative procedure

Water-Demand Forecast

Demand forecasting plays an important role in the efficient management of a DWN since it allows programming of the pumping arrangements over the next 24 h, taking advantage of the electricity tariff structure. A review of the scientific literature confirms that a considerable amount of effort has been expended on water-demand forecasting. In the case of operational control, the interest is restricted to short time scale (hourly/daily) rather than annual/monthly used for longer-term water-resources planning. Most of the developed methodologies for hourly forecasts exploit the recurring patterns and periodicities that exist in water-demand data at different levels of temporal aggregation. A detailed analysis of the observed hourly and daily water-demand time series revealed the existence of patterns in which it is possible to identify seasonal and weekly periodicities in daily water demands as well as daily periodicities in hourly water demands. Figure S1 shows a demand profile corresponding to the 24-h demand distribution in one demand sector. Similar demand patterns are used on all demand locations. From the literature analysis, the most used methods developed for short-term demand forecast relies on the combined used of time-series analysis and demand patterns [17], [45].

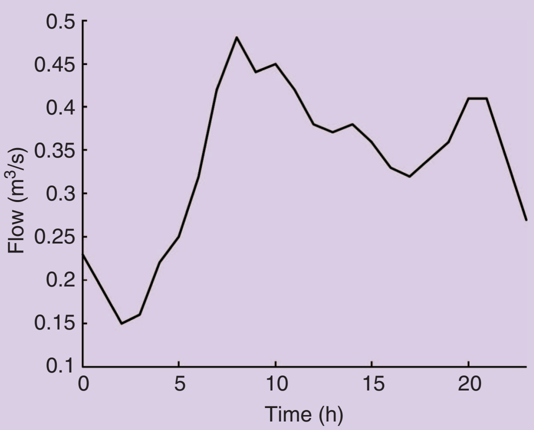

FIGURE S1 Hourly pattern of a demand sector that repeats periodically every day.

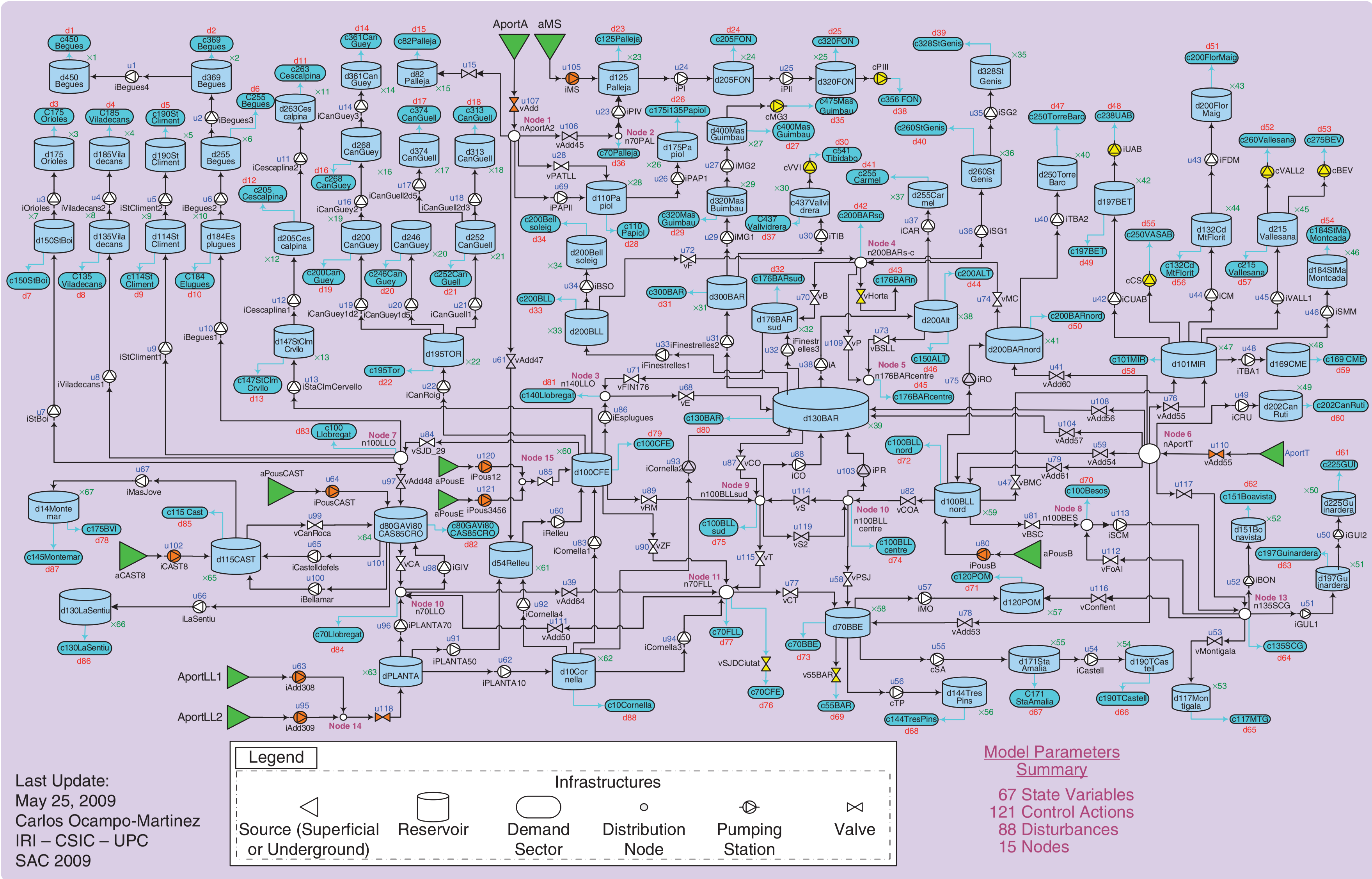

FIGURE 5 The Barcelona DWN is managed by the AGBAR water company that supplies drinking water to Barcelona city and its metropolitan area. The main sources of water are the Ter and Llobregat rivers, which are regulated at their head by some dams with an overall capacity of 600 hm^3. Currently, there are four drinking water treatment plants (WTP): the Abrera and Sant Joan Despí plants, which extract water from the Llobregat river; the Cardedeu plant, which extracts water from the Ter river; and the Besòs plant, which treats the underground flows from the aquifer of the Besòs river. There are also several underground sources (wells) that can provide water through pumping stations. Those different water sources currently provide a flow of around 7 m^3/s. The most important sources in terms of capacity are the Sant Joan Despí and Cardedeu plants. The maximum flow that can be taken from the first is about 5 m^3/s, while the maximum flow from the second is about 7 m^3/s. The water price from each source is different depending on water treatments and legal extraction canons.

follows that consists of 1) finding a search direction through the use of the Jacobian of the constraints, the selection of a set of basic variables, and the computation of the reduced gradient and 2) performing a search in this direction, through a pseudo-Newton process, until a convergence criterion is met. A description of the algorithm and its implementation may be found in the GAMS solver manuals and deeply reported in [40].

The mathematical models have been obtained by using the modeling methodologies described in this article. Real data collected from the SCADA associated to the Barcelona drinking water and SN have been used. For the case of the DWN, the real data corresponds with the water demand of the network users during several years and with the information of performance of the local controllers at the network actuators (valves and pumping stations). On the other hand, real data from the SN corresponds with measurements of rain sensors during several years. The sewage system has been simulated by using a high-fidely model implemented in MOUSE and developed by CLABSA company. On the other hand, the DWN has been simulated with a detailed SIMULINK model, which has been validated by the AGBAR company against their historic data.

TABLE 2 Closed-loop performance results (all values in e.u.).

Demand Episodes	Current Control Water	Current Control Electricity	Current Control Total	MPC Control Water	MPC Control Electricity	MPC Control Total
2007-07-23	514	257	770	268 (−48%)	229 (−11%)	497 (−55%)
2007-07-24	508	273	781	339 (−33%)	231 (−15%)	560 (−37%)
2007-07-25	519	251	770	317 (−39%)	228 (−9%)	545 (−41%)
2007-07-26	537	246	783	324 (−40%)	229 (−7%)	553 (−41%)

Results with the Barcelona DWN

Using the modeling methodology, a control-oriented model for the Barcelona complete transport network was built (see Figure 5). This model considers 63 storage tanks (states), three surface sources and six underground sources, 79 pumps, 50 valves, 18 nodes, and 88 demands (disturbances). Using this model, the control strategies for the network actuators are obtained. In this case study, the prediction horizon is 24 h, due to the daily periodicity of demands and operation. Regarding the value of H_u, it was set to be equal to H_p, following the operational needs of the DWN management. A demand forecast during this horizon is provided by a demand system based on time series techniques described in the modeling section [15], [17]. (See "Water-Demand Forecast.")

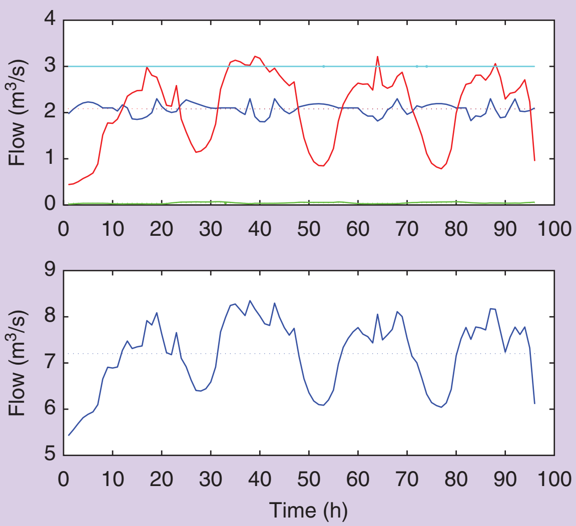

FIGURE 6 Inflows from the network sources. In (a), the water supplies are shown in red for the Ter river, in blue for the Sant Joan Despí superficial source, in cyan for the Sant Joan Despí underground, and in green for the Abrera treatment plant. In (b), the sum of all flows and its average is shown. The mean flow from Llobregat source is about 5 m^3/s, while the rest of water needed to satisfy the total demand is taken from the Ter and Abrera sources. The water flow from underground sources is penalized to avoid their overexploitation. In fact, these sources are rarely used.

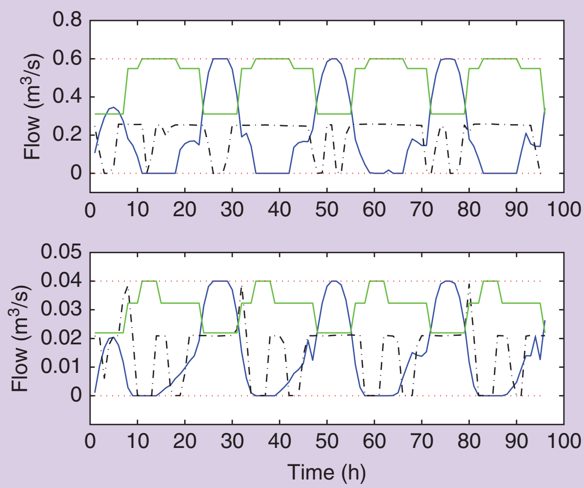

FIGURE 7 Electrical fee effects on pumps operation. In both graphs the scaled electric cost is shown in green and the real flow, which corresponds with data from the real actuator manipulation performed by the company, is shown in a dotted-dashed black line. The optimized flow determined by the MPC controller is shown in blue. Part (a) corresponds with the outflow from the Finestrelles pumping station, while part (b) shows the outflow from the Santa Coloma Cervelló pumping station. When MPC is considered, the pumping stations work during the time interval with the cheapest economic cost, if possible. For instance, the flow pumped by the Santa Coloma Cervelló pumping station decreases during those periods where the economic cost is not minimal. In contrast, there is not enough flow from the Finestrelles pumping station if water is only pumped during the cheapest period of economic costs. Hence, this pumping station must pump water during other periods but the flow rate is lower.

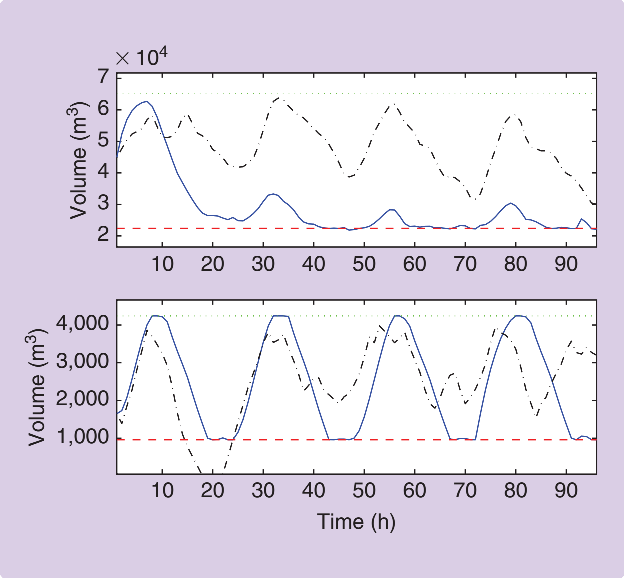

FIGURE 8 Volume evolution of some tanks. In both graphs, the real volume is shown in a dotted-dashed black line, the optimized volume is show in blue, and the penalization volume is shown in a dashed red line. Part (a) corresponds with the tank d200ALT, where the MPC controller makes the volume lower than the real operation performed by the management company, which yields less economic costs of water transport while decreasing the system safety against failures. Part (b) corresponds to the tank d70BBE, where the volume never violates the constraints imposed by the MPC controller, in contrast with the real data.

Results obtained using the designed MPC are compared with those obtained employing the current local control approach. The local control is based on proportional-integral-derivative (PID) controllers, whose objective was to maintain the water level in the tanks inside pre-established bounds, which might vary during the day to take into account the demand variation by pumping more or less water. The comparison is between the performance reached by the local PID controllers already in place and tuned by the company experts, and the global (supervisory) MPC controller providing optimal set points to the currently existing PID control loops. Basically, it is a comparison of loops with and without supervisory control. Centralized and decentralized control approaches are not in the scope of this article but have been compared and discussed in the Barcelona DWN case study [41], [42].

Table 2 summarizes the control results in terms of performance (water and electrical cost) over four days of typical demand. The water supplied for these four days is shown in Figure 6. In Table 2, the performance indices representing costs are given in economic units (e.u.) instead of a currency due to confidentiality restrictions.

From Table 2, it can be noticed that

1) MPC produces an improvement in the reduction of water costs, between the 30% and the 50% with regard to the current control with fixed real flows since the optimizer can maximize the water source contribution, if possible. However, this is not always possible due to legal and contractual reasons not related to the network characteristics (operational limits of actuators and tanks).
2) MPC minimizes the electrical costs by pumping as much as possible during the cheapest time period (typically during nights).

Figure 6 shows the evolution of the flow from all sources when MPC is used. Figure 7 compares the operation of some representative pumping stations when the current control—the control strategy used by the management company—and MPC are used. Finally, Figure 8 shows the volume evolution of some network tanks, as well as their maximum and safety volumes when each of these control strategies are used.

Results with the Barcelona SN

The city of Barcelona has a combined sewage system (CSS) of approximately 1697-km length in the municipal area plus 335 km in the metropolitan area, but only 514.43 km are considered as the main SN. Barcelona has a population around 1.59 million inhabitants on a surface of 98 km^2, which is a very high population density. The yearly rainfall is not very high (600 mm/yr) but includes heavy storms (up to 90 mm/h) typical of the Mediterranean climate that can cause a lot of flooding problems and CSO to the receiving environment. CLABSA is the company in charge of the sewage system management in Barcelona. Their remote control system has been in operation since 1994, which includes sensors, regulators, remote stations, communications, and a control center. Nowadays, the urban drainage system contains 21 pumping stations, 36 gates, ten valves, and eight detention tanks, which are regulated to prevent flooding and CSO. The remote control system is equipped with 56 remote stations, including 23 rain gauges and 136 water-level sensors. These latter elements provide real-time information about rainfall and water levels into the sewage system. All the information is centralized at the control center through a SCADA system. The regulated elements—pumps, gates, and detention tanks—are currently controlled locally; that is, they are handled from the remote control center according to the measurements of sensors connected only to local stations.

From the whole SN of Barcelona, this article considers a portion that is representative of the main phenomena and the most common characteristics of the entire network. For this representative portion, shown in Figure 9, a calibrated and validated model of the network is available. This model has been obtained using the virtual modeling methodology and rain-gauge data corresponding to an interval of several years.

Using this model, an MPC controller is designed to provide the set points for the network actuators (local control loops). The corresponding H_p is 30 min (six samples), with a sampling time of 5 min. A rain forecast during this horizon may be provided by an external rain forecasting system based on a meteorological radar, if available, or it may be computed internally using a sample-hold assumption [43]. (See "Rain Intensity Forecast.")

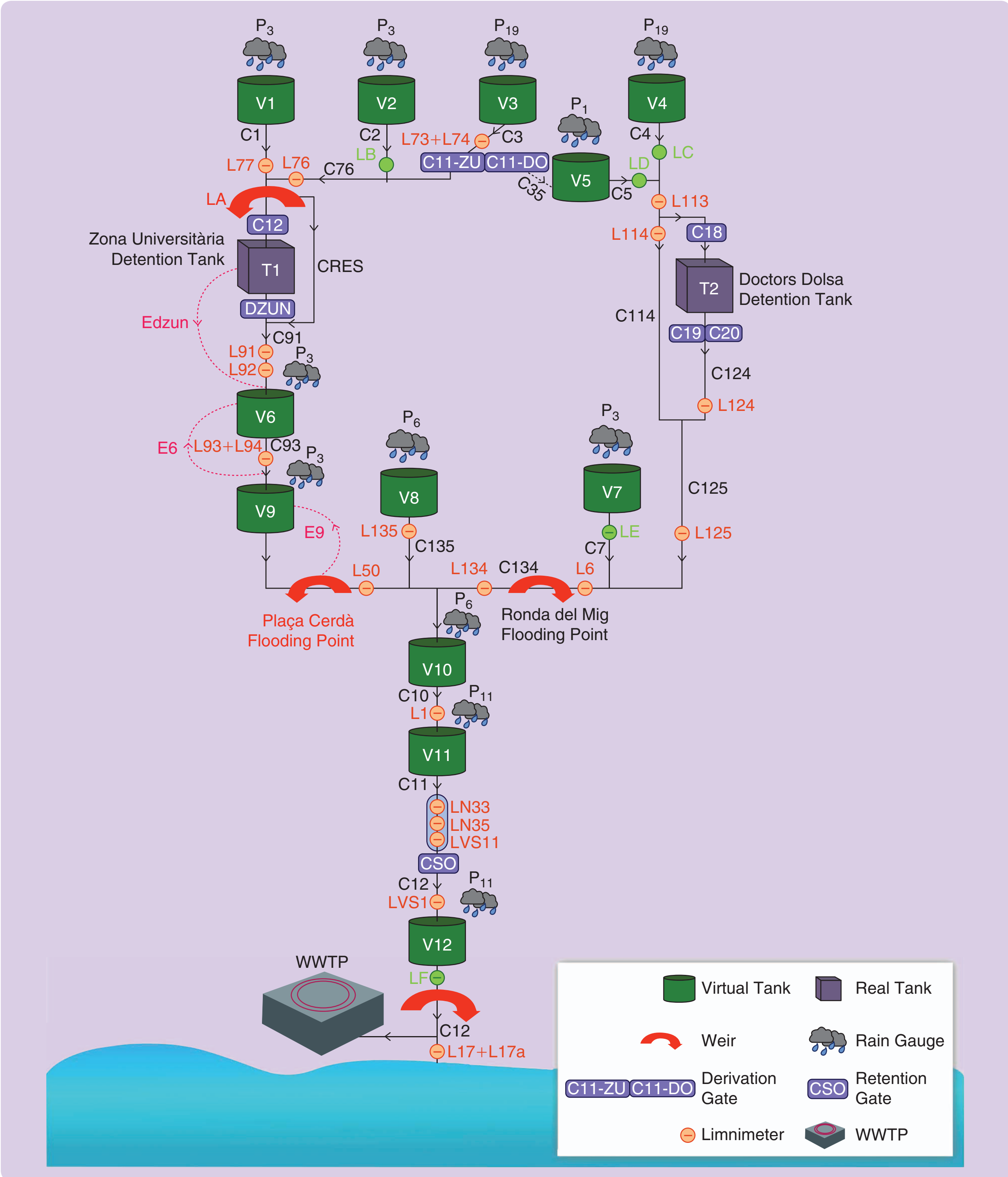

FIGURE 9 The considered Barcelona Test Catchment (BTC) has two detention tanks: Zona Universitaria Detention Tank (T_1) and Doctors Dolsa Detention Tank (T_2). Additionally, one large sewer—marked as CSO sewer—with an associated detention gate, is used as additional storage capacity. This procedure is called in-line detention. The detention gates operating with global control are at the output of detention tanks (C_{15} and C_{19}), the in-line detention gate (CSO), and the flow diversion gate (C_{11}), which connects the two detention tanks. Eleven measurement points are considered for flooding control in the case of the global control strategy. A waste water treatment plant (WWTP) with a maximum treatment capacity of 2 m^3/s is located at the end of the BTC. Flows to the WWTP that are bigger than this maximum value are released to the sea, generating CSO. Using the virtual tank approach, the BTC model has 12 state variables corresponding to the volumes in the 12 tanks (two real, ten virtual), four control inputs corresponding to the gates, and five measured disturbances corresponding to measurements of rain precipitation at the subcatchments of the BTC.

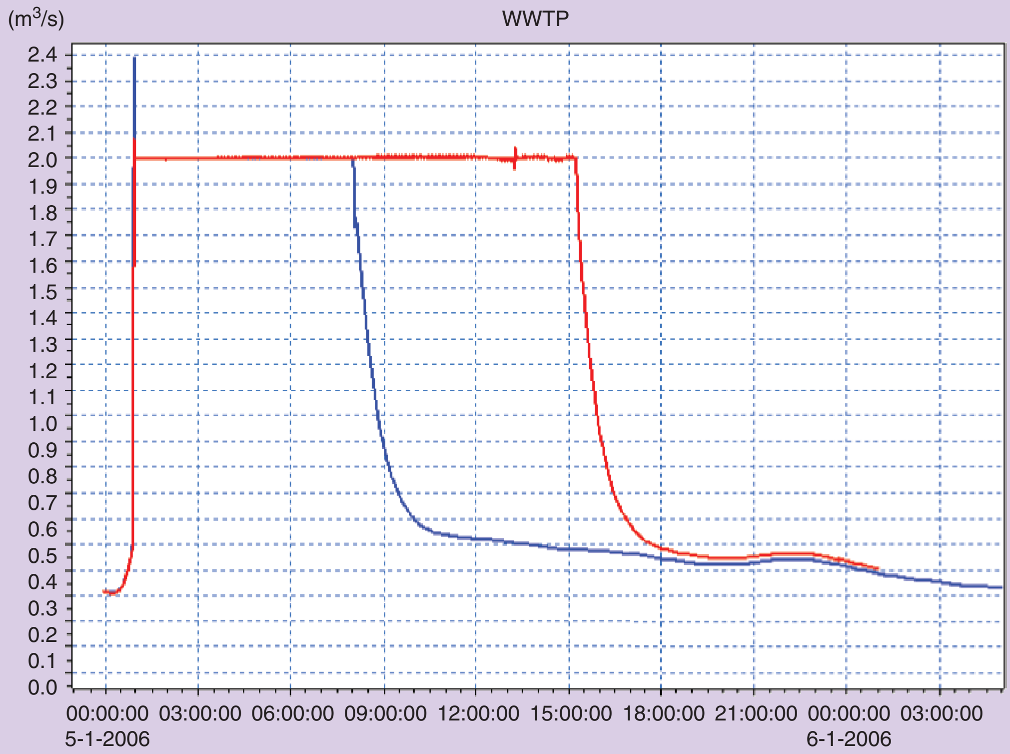

FIGURE 10 Comparison of WWTP volume in local and global control, shown in blue and red, respectively. It can be noticed that the WWTP is used for a longer time at the maximum capacity in global control than when only local control is used, reducing the pollution to the sea.

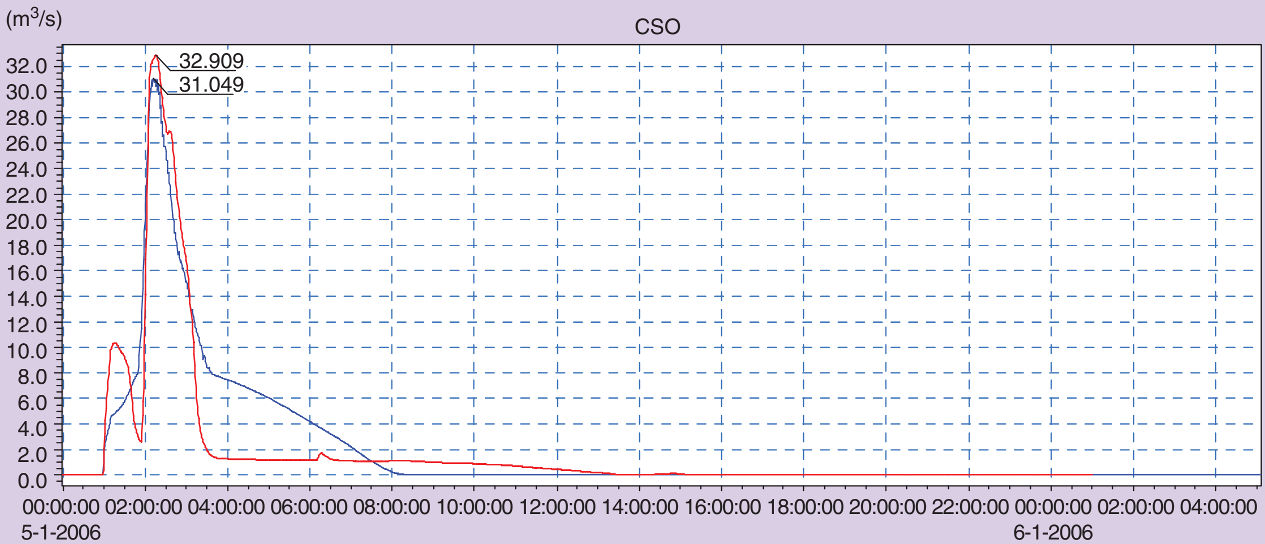

FIGURE 11 Comparison of the CSO volume to the sea in local and global control, shown in blue and red, respectively. The global control reduces significantly the volume of CSO (pollution to the sea) in this scenario compared to the local control. This improvement is achieved due to the better usage of the on-line retention capacity of the network.

To compare the performance of the current control strategy based on local controllers with the designed MPC strategy for global management, three different real rain scenarios are considered.

Rain Scenario 1 (05/01/2006)

This is a common winter rain that occurring in Barcelona (approximately a two-month average *return period*). It is neither very intense nor very long. The maximum intensity occurs in rain gauge P_{11} (see Figure 9), with 49.2 mm/h, and its duration is about 3 h. This rain does not cause flooding, so the interest for the test is to avoid CSO spills.

Rain Scenario 2 (12/09/2006)

This is a common summer rain occurring in Barcelona (approx. 1-yr return period). It is intense and longer. The maximum intensity occurs in rain gauge P_3 (see Figure 9), with 128.4 mm/h, and its duration is about three days but with periods of no rain. This rain may cause flooding if the management of detention tanks is not appropriate, so the interest for the test is to manage flooding and also to avoid CSO spills.

Rain Scenario 3 (31/07/2002)

This is a short and very intense rain. It has an average return period of about eight years. This rain causes flooding. The main performance expected is during the first hours of the event; control devices must be managed so that flooding is minimized and, after the rain event, the CSO spill are highly minimized.

Figure 10 shows that more volume of water is treated by the WWTP when MPC is used, while Figure 11 shows the comparison of CSO volumes in the rain scenario 3. The global management reduces significantly the volume of CSO in this scenario. The WWTP operational constraints are satisfied when the global control is used since they are imposed as constraints in the MPC strategy.

Table 3 presents the results obtained with the different rain scenarios using the current local control strategy and the global control based on MPC. Looking at these results, the following observations can be made:

1) In terms of the water volume treated by the WWTP, the global control strategy always outperforms the local control in all the considered scenarios.
2) The CSO spill released to the sea is significantly reduced by the global control in all scenarios.
3) Flooding is also reduced by the global control strategy based on MPC compared to the local control strategy, although the rain scenarios 12/09/2006 and 31/07/2002 still cause some flooding due to limitations on the infrastructure.

CONCLUSIONS

The increasing use of advanced information and communication techniques to manage water systems contributes, to a great extent, to achieving environmental and social goals in several fields (see, for instance, [44]). This article shows how the concepts of MPC can be used to efficiently solve complex management problems in real systems of the UWC. Particularly, this control technique allows to consider different issues on the behavior of these networked

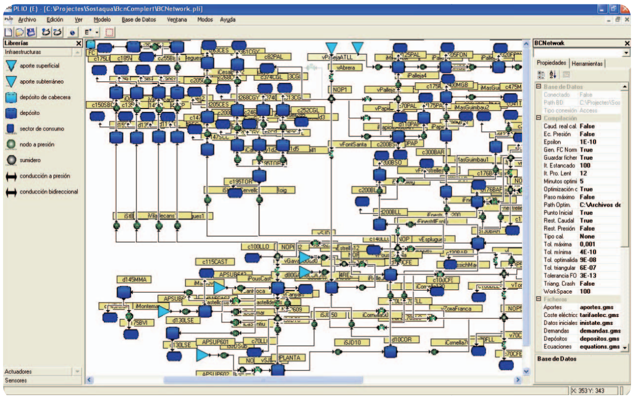

FIGURE 12 PLIO interface corresponding to the model manager module then allows creating/updating the model of the water network in a user-friendly way.

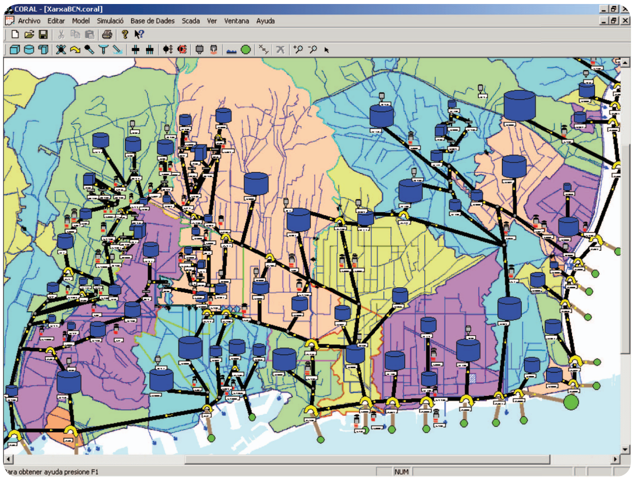

FIGURE 13 CORAL interface corresponding to the model manager module then allows creating/updating the model of the SN in a graphical way using the virtual modeling approach.

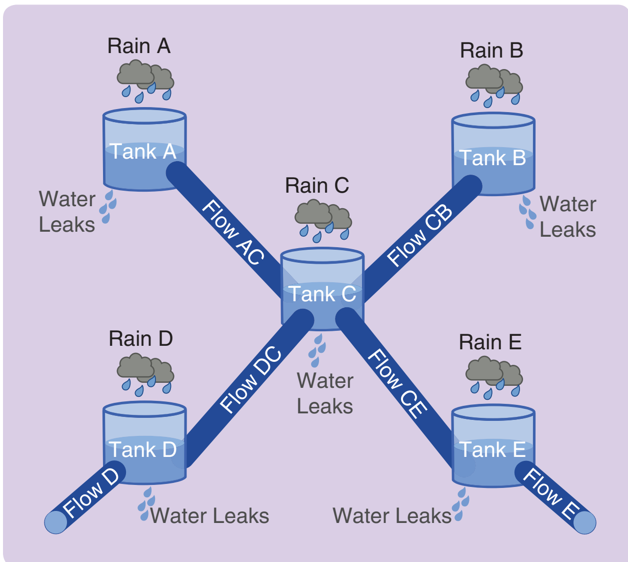

FIGURE 14 SN modeling by means of interconnected virtual tanks. Each tank represents a catchment in the SN.

Rain-Intensity Forecast

Radar and rain gauges are the most common measurements for collecting rainfall data. Together with rainfall radar, rain gauges are widely used to estimate the areal and spatial distribution of rainfall. Unlike rainfall radar, which can estimate rainfall at a high resolution over a large area, rain gauges can only measure rainfall directly at point locations (see Figure S2 to observe rainfall readings provided by the rain gauges of the Barcelona SN during a real rain scenario). As a remote sensing observation, rainfall radar can allow the prediction of short-term forecasts based on the current weather situation, which can provide useful information on rainfall distribution. Rainfall occurrence in a particular area can be studied to provide the rainfall rate that can then be used in the future for predicting rainfall levels for similar weather situations. Although radar detection is affected by problems such as ground occlusion and altitude effects, it could be very useful and efficient in short-term forecasting, which is also called nowcasting. Weather radars transmit a pulse of radio waves and detect any rainfall mass through the detection of electromagnetic reflection. More precisely, a reflectivity-rainfall (Z–R) relationship is built to produce reliable radar-based predictions of rainfall intensities by applying radar reflectivity data. The rain intensity R is related to the radar reflection Z according to the power law. The rainfall amounts can be estimated by involving the use of reflection by means of the Z–R relation. In this way, the weather radars have the potential to estimate the rainfall. Recently, it has been proved that the prediction based on weather radar yielded a satisfactory result with a small average error rate and also proved to be accurate—even more accurate in totaling rainfall than rain gauge models in some cases.

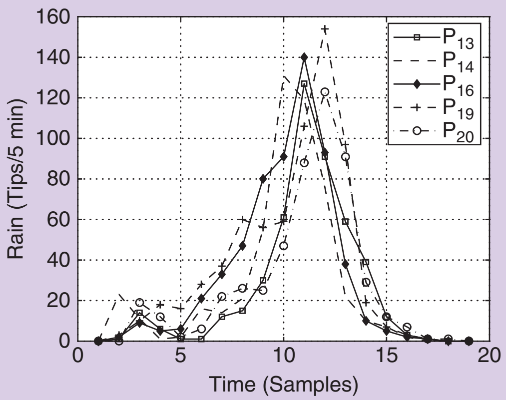

FIGURE S2 Heavy rain scenario occurring in Barcelona on September 14, 1999. The big peak of rain is in a very short time period.

systems and to cope with different intrinsic characteristics that cannot be treated by using other control strategies.

The different intrinsic characteristics of DWNs and SNs have been described and appropriate mathematical solutions to tackle them have been presented. Similarly, realistic operational goals of DWNs and SNs have been outlined and modeled. This article shows the results obtained by applying the MPC with the previously described approaches in two realistic cases taken from the corresponding networks in Barcelona.

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TABLE 3 Closed-loop performance result for some rain episodes (all values in cubic hectometers).

	Current Control			MPC Control		
Rain Episodes	Flooding	Pollution	Treated W.	Flooding	Pollution	Treated W.
05/01/2006	0	203	77	0	167 (–17%)	116 (33%)
12/09/2006	5662	740	352	4072 (–28%)	670 (–9%)	404 (12%)
31/07/2002	5553	643	144	5436 (–2%)	588 (–8%)	198 (27%)

AUTHOR INFORMATION

Carlos Ocampo-Martinez received his electronic engineering degree and his M.Sc. degree in industrial automation from the National University of Colombia, Campus Manizales, in 2001 and 2003, respectively. In 2007, he received his Ph.D. degree in control engineering from the Technical University of Catalonia (Barcelona, Spain). After a year as postdoctoral fellow of the ARC Centre of Complex Dynamic Systems and Control (University of Newcastle, Australia), he was with the Spanish National Research Council (CSIC) at the Institut de Robòtica i Informàtica Industrial (IRI) in Barcelona as a *Juan de la Cierva* research fellow. Since 2011, he is assistant professor at the Technical University of Catalunya, Automatic Control Department (ESAII). His main research interests are in the areas of constrained MPC, large-scale systems management, nonlinear dynamics, and industrial applications.

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(*continued on page 41*)

Q. What are some of the most promising opportunities you see in the control field?

Guoxiang: I would say networked control systems and industrial applications. Time has come to run control systems over networks. Industrial applications present us with ample research opportunities.

Q. You are the author of two books in the control field. What topics do these books cover?

Guoxiang: I coauthored a book on control-oriented system identification that summarizes most of my early works. The book covers identification methods based mostly on frequency response data that emerged in the 1990s under the H-infinity framework. Recently I published another book that covers discrete-time linear systems with applications to feedback control and data communications. This book partially contains my work in the past decade.

Q. What are some of your interests and activities outside of your professional career?

Guoxiang: My interest outside of my professional career lies mainly in ancient Chinese history and poetry. Although I do not understand much, I enjoy reading both.

Q. Thank you for your comments.

Guoxiang: I greatly appreciate *IEEE Control Systems Magazine* giving me the opportunity to speak to its audience.

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