Temporal multi-level coordination techniques oriented to regional water networks: application to the Catalunya case study

Cong Cong Sun, Vicenç Puig and Gabriela Cembrano

ABSTRACT

In this paper, a multi-layer model predictive control (MPC) with temporal multi-level coordination for regional water supply systems is proposed. First, a multi-layer control structure resulting from a functional decomposition of water network is briefly presented. Inside each layer, an MPC based controller is used. Between related layers, a temporal multi-level coordination mechanism is used to generate control strategies which consider objectives and time scales of both layers. The upper layer which is named supply layer works in a daily scale in order to achieve the global management policies for the different reservoirs. The lower layer which is named transportation layer works in an hourly scale and is in charge of manipulating the actuators (pumps and valves) set-point to satisfy the local objectives. The results of the modelling will be applied to the Catalunya Regional Water Network and this paper presents the simulation results based on an aggregate model of this network.

Key words | multi-layer MPC, regional water network, temporal multi-level strategy

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INTRODUCTION

Complex regional water supply system management is an important research topic because of the significance of water for human beings.

From a functional perspective, a regional water network can be structurally organized into three layers (Ocampo-Martinez *et al.* 2013):

- Supply layer, composed of water sources, large reservoirs and also natural aquifers.
- Transportation layer, linking water treatment and desalinization plants with reservoirs distributed all over the city.
- Distribution layer, used for meeting consumer demands.

Each of the layers of a regional water network must be operated at different time scale because of the different dynamics they present according to their specified objectives. In general, these layers are often separately operated. What is more, the ecological effect and also sustainable usages of water which are important have seldom been included (Brdys & Ulanicki 1994; Cembrano *et al.* 2005; Ocampo-Martinez *et al.* 2013). The coordinated operation of different layers in a regional network is one of the main motivations for the research reported in this paper.

In most water systems, the actuators, named valves, turbines, pumps, gates and retention devices, are controlled locally (using simple control laws such as proportional-integral-derivative (PID) controllers), that is, they are controlled by a remote station according to the measurements of sensors connected only to that station. However, a global real-time control system requires the use of an operational model of the system dynamics in order to compute, ahead in time, optimal control strategies for the actuators based on the current state of the system provided by supervisory control and data acquisition sensors, the current disturbance measurements and appropriate disturbance predictions. The computation of an optimal global control law should take into account all the physical and operational constraints of the dynamical system, producing set-points which cause certain control objectives to be achieved.

Model predictive control (MPC) has been proven to be one of the most effective and accepted control strategies for

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the global optimal operational control of large-scale water networks (Ocampo-Martinez *et al.* 2013). Applications to different large-scale infrastructures such as drinking water networks (Brdys & Ulanicki 1994), sewer networks (Marinaki & Papageorgiou 2005), open-flow channel networks (Overloop 2006) or electrical networks (Negenborn 2008) prove the advantages of this technique. One of the main reasons for its success is that once the plant dynamical model has been obtained, the MPC design consists of expressing the desired performance specifications through different control objectives (e.g. weights on tracking errors and actuator efforts as in classical linear quadratic regulation), and constraints on system variables (e.g. minima/maxima of selected process variables and/or their rates of change) which are necessary to ensure process safety and asset health. The rest of the MPC design is straightforward: the given model, constraints and weights define an optimal control problem over a finite time horizon in the future (for this reason the approach is called predictive). This is translated into an equivalent optimization problem and solved online to obtain an optimal sequence of future control actions. Only the first of these actions is applied to the process, as at the next time step a new optimal control problem is solved, to exploit the information coming from fresh new measurements. In this way, an open-loop design methodology (i.e. optimal control) is transformed into a feedback one.

In the recent literature, there has been a renewed interest in multi-layer MPC either from industrial practice or from academia (Tatjewski 2008; Scattolini 2009). This is especially the case when a system is composed of subsystems with multiple time scales as in the case of the regional water networks. A straightforward task of designing and implementing a single centralized control unit is too difficult, as discussed in Brdys *et al.* (2008), because the required long prediction horizon and short control time steps might lead to an optimization problem of very high dimension and under large uncertainty radius. A way to cope with this problem is to apply a hierarchical control structure based on decomposing the original control task into a sequence of different, simpler and hierarchically structured subtasks, handled by dedicated control layers operating at different time scales (Brdys & Tatjewski 2005).

The main contribution of this paper is proposing a temporal multi-layer hierarchical MPC scheme for regional water networks which, according to the literature review, has never been applied before to this type of water networks. The proposed strategy will coordinate the MPC controllers for the supply and transportation layers by means of a temporal hierarchical sequence of optimizations and constraints going from the upper to the lower layer. The Catalunya Regional Water Network is used as a case study to validate the proposed control scheme.

The paper is organized as follows. The section below introduces the control-oriented modelling methodology proposed for regional water networks followed by MPC techniques and MPC models for the supply and transportation layers. After that, multi-layer MPC and temporal multi-level coordination techniques are outlined and then the formulations of temporal multi-level coordination for regional water network and predicting water demand for regional water network are presented. The considered case study based on the Catalunya Regional Water Network is next described and then the simulation results of the proposed approach as applied to Catalunya Regional Water Network are outlined. In the final section, the main conclusions are presented.

CONTROL-ORIENTED MODELLING METHODOLOGY

Complex nonlinear models are very useful for off-line operations (for instance, calibration and simulation). Fine mathematical representations such as the Saint-Venant equations for describing the open-flow behaviour (Mays 2004) or pressure-flow models allow the simulation of those systems with enough accuracy to observe specific phenomena, useful for design and investment planning. However, for online computation purposes such as those related to global management, a simpler control-oriented model structure should be conveniently selected. This simplified model includes the following features:

- *Representation of the main network dynamics*: It must provide an evaluation of the main representative hydrological/hydraulic variables of the network and their response to control actions at the actuators.
- *Simplicity, expendability, flexibility and computational speed*: It must use the simplest approach capable of

achieving the given purposes, allowing very easily to expand and/or modify the modelled portion of the network.

Several modelling techniques dealing with the operational control of water systems have been presented in the literature (see Brdys & Ulanicki (1994), Mays (2004) and the references therein). Here, a control-oriented modelling approach is outlined, which follows the principles presented in Cembrano *et al.* (2004) and Ocampo-Martinez *et al.* (2013). The extension to include the pressure-model can be found in the references provided by Brdys & Ulanicki (1994) and Mays (2004).

A water system generally contains tanks, which store the drinking water that comes from the network sources, a network of pipes and open flow canals, and a number of demands. Valves and/or pumping stations are elements that allow manipulation of the water flow according to a specific policy and to supply water requested by the network users. These flows are chosen by a global management strategy.

The water system model can be considered as composed of a set of constitutive elements, which are presented and discussed below.

Dams, tanks and reservoirs

Water dams, tanks and reservoirs provide the entire network with the water storage capacity. The mass balance expression relating the stored volume v, the manipulated inflows $q_{\text{in}}^{i,j}$ and outflows $q_{\text{out}}^{i,l}$ (including the demand flows as outflows) for the ith storage element can be written as the discrete-time difference equation

$$v_i(k+1) = v_i(k) + \Delta t\left(\sum_j q_{\text{in}}^{i,j}(k) - \sum_l q_{\text{out}}^{i,l}(k)\right) \tag{1}$$

where Δt is the sampling time and k denotes the discrete-time instant. The physical constraint related to the range of admissible water in the ith storage element is expressed as

$$\underline{v}_i \leq v_i(k) \leq \bar{v}_i, \quad \text{for all } k, \tag{2}$$

where $\underline{v}_i$ and $\bar{v}_i$ denote the minimum and the maximum admissible storage capacity, respectively. As this constraint is physical, it is impossible to send more water to a storage element than it can store, or draw more water than the stored amount. Although $\underline{v}_i$ might correspond to an empty storage element, in practice this value can be set as nonzero in order to maintain an emergency stored volume enough to supply for facing extreme circumstances.

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

Actuators

Two types of control actuators are considered: valves/gates and pumps (more precisely, complex pumping stations). The manipulated flows through the actuators represent the manipulated variables, denoted as q_u. Both pumps and valves/gates have lower and upper physical limits, which are taken into account as system constraints. As in (2), they are expressed as

$$\underline{q_{u_i}} \leq q_{u\,i}(k) \leq \overline{q_{u\,i}}, \quad \text{for all } k, \tag{3}$$

where $\underline{q_{u_i}}$ and $\overline{q_{u\,i}}$ denote the minimum and the maximum flow capacity, respectively.

Nodes

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

$$\sum_j q_{\text{in}}^{i,j}(k) = \sum_h q_{\text{out}}^{i,h}(k) \tag{4}$$

From now on and with some abuse of notation, node inflows and outflows are still denoted by q_{in} and q_{out}, respectively, despite the fact that they can be manipulated flows and hence denoted by q_u, if required.

River reaches

A single canal reach can be approximated by using the modelling approach proposed by Litrico & Fromion (2004) that leads to the following relation between the upstream (q_{ups}) and downstream (q_{dns}) flows

$$q_{\text{dns}}(k+1) = a_1 q_{\text{dns}}(k) + b_0 q_{\text{ups}}(k-d) \tag{5}$$

where $d = \tau_d/T_s$, τ_d is the downstream transport delay, T_s is the sampling time, $b_0 = 1 - a_1$ and $a_1 = e^{-T_s/T}$.

Demand and irrigation sectors

Demand and irrigation sector represents the water demand made by 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 in urban areas can be anticipated by a forecasting algorithm that is integrated within the MPC closed-loop architecture. The demand forecasting algorithm typically uses a two-level scheme composed of (i) a time-series model to represent the daily aggregate flow values and (ii) a set of different daily flow demand patterns according to the day type to cater for different consumption during the weekends and holiday periods. Every pattern consists of 24 hourly values for each daily pattern (Quevedo *et al.* 2010). This 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. On the other hand, irrigation demand is typically planned in advance with farmers. Pre-established flows for irrigation are in the irrigation areas in certain periods of the year.

MPC MODELLING FOR SUPPLY AND TRANSPORTATION LAYERS

Model predictive control

MPC is one of the most advanced control methodologies which have made a significant impact on industrial control. MPC does not consider a specific control strategy but a very wide range of control methods which make an explicit use of the process model to obtain the control signal by minimizing an objective function which represent the desired control goals. MPC can handle multi-variable control problems and it can consider actuator limitations as well as operational and physical constraints.

The standard MPC problem based on the linear discrete-time prediction model is considered as described in Maciejowski (2002)

$$x(k+1) = Ax(k) + Bu(k), \tag{6a}$$

$$y(k) = Cx(k), \tag{6b}$$

where $x(k) \in \mathbb{R}^{n_x}$ is the state vector and $u(k) \in \mathbb{R}^{n_u}$ is the vector of command variables at time step k, and $y(k) \in \mathbb{R}^{n_y}$ is the vector of the measured output. Following the formalism provided by Maciejowski (2002) for the basic formulation of a predictive control, the cost function is assumed to be quadratic and the constraints are in the form of linear inequalities. Thus, the following basic optimization problem (BOP) has to be solved

$$\min_{(u(0|k),\cdots,u(H_p-1|k))} J(k) \tag{7a}$$

$$s.t. \quad x(i+1|k) = Ax(i|k) + Bu(i|k), \quad i = 1, \cdots, H_p,$$

$$x(0|k) = x_k, \tag{7b}$$

$$x_{\min} \le x(i|k) \le x_{\max}, \quad i = 1, \cdots, H_p,$$

$$u_{\min} \le u(i|k) \le u_{\max}, \quad i = 0, \cdots, H_{p-1},$$

As described above, J is a performance index, representing the operational goals of the system. And H_p is the prediction horizon, $x(0)$ is the initial condition of the state vector, $u_{\min}$ and $u_{\max}$ are known vectors defining the saturation constraints on inputs variables (operational ranges). Problem (7) can be recast as a quadratic programming (QP) problem, whose solution

$$\mathcal{U}^*(k) \triangleq [u^*(0|k) \cdots u^*(H_p-1|k)]^T \in \mathbb{R}^{H_p m \times 1} \tag{8}$$

is a sequence of optimal control inputs that generates an admissible state sequence. At each sampling time k, Problem (7) is solved for the given measured (or estimated) current state $x(k)$. Only the first optimal move $u^*(0|k)$ of the optimal sequence $\mathcal{U}^*(k)$ is applied to the process

$$u_{MPC}(k) = u^*(0|k) \tag{9}$$

The remaining optimal decisions are discarded and the optimization is repeated at time $k+1$.

State space model for supply layer

The state space model of supply layer has two kinds of states and control variables. The first kind of state variable represents reservoirs and the managed variable corresponds to actuator flows

$$x(k+1) = A\,x(k) + B\,u(k) + B_p[d(k) - \varepsilon(k)], \quad k \in \mathbb{Z} \tag{10}$$

where, $x(k) \in \mathbb{R}^{n_x}$ state variables represent volumes, $u(k) \in \mathbb{R}^{n_u}$ control corresponds to actuator flows, $d(k) \in \mathbb{R}^{n_d}$ disturbances correspond to demands, $\varepsilon(k) \in \mathbb{R}^{n_d}$ slack variables for unsatisfied demands.

At this function, $\varepsilon(k)$ is introduced to control the amount of demand which has not been satisfied.

The second kind of states and control variable represent river flows in a river reach model with delays. For simplicity and brevity of the explanation, consider river reach model (5) as a transport delay (Evans *et al.* 2011)

$$q_{\text{out}_i} = q_{\text{in}_i}(k - \tau_d) \tag{11}$$

where τ_d represents the delayed value. For time delays associated with flows within the network, the following auxiliary state equations are introduced

$$x_{j,1}(k+1) = q_j(k) \tag{12}$$

$$x_{j,i+1}(k+1) = x_{j,i}(k),\ i = 1,\ \cdots,\ \tau_d \tag{13}$$

where, $x_{j,i}(k) \in \mathbb{R}^{n'_x}$ state variables represent flows, $q_j(k) \in \mathbb{R}^{n'_u}$ flows, part of control variables, $\tau_d \in \mathbb{Z}$ delay.

More details on how this approach can be extended to the case that river reach model (5) is not just considered as a delay can be found in Evans *et al.* (2011).

After combining (12) and (13) with (10), we have a new augmented state space representation

$$\tilde{x}(k+1) = \widetilde{A}\,\tilde{x}(k) + \widetilde{B}\,\tilde{u}(k) + \widetilde{B}_p\,[d(k) - \varepsilon(k)], \quad k \in \mathbb{Z} \tag{14}$$

where

$$\tilde{x}(k) = \begin{bmatrix} x(k) \\ x_{j,i}(k) \end{bmatrix}, \quad \tilde{u}(k) = \begin{bmatrix} u(k) \\ q_j(k) \end{bmatrix}$$

and

$$\tilde{x}(k) \in \mathbb{R}^{\tilde{n}_x}$$
$$\tilde{u}(k) \in \mathbb{R}^{\tilde{n}_u}$$

According to (2) and (3), all the variables are subject to the following inequality constraints

$$\tilde{x}_{\min} \le \tilde{x}(k) \le \tilde{x}_{\max} \tag{15}$$

$$\tilde{u}_{\min} \le \tilde{u}(k) \le \tilde{u}_{\max} \tag{16}$$

$$\varepsilon_{\min} \le \varepsilon(k) \le \varepsilon_{\max} \tag{17}$$

where $\tilde{x}_{\min}$ and $\tilde{x}_{\max}$ are physical limitations of the reservoirs, while $\tilde{u}_{\min}$ and $\tilde{u}_{\max}$ are physical limitations of the river flows. The range of $\varepsilon_{\min}$ lies between zero and the related demand.

As described in the section 'Control-oriented modelling methodology', the balance at every node should be satisfied, where E, E_d, $E_{\tilde{x}}$ are matrices which parameters can be obtained from topology of the water network

$$E\,\tilde{u} + E_d\,d - E_d\,\varepsilon + E_{\tilde{x}}\,\tilde{x} = 0$$

During the consumption process, water storage of reservoirs should be kept above a given level (named as water safety level) which is used as an emergency supply for a drought period. Any situation below the emergency level should be penalized using soft constraints

$$\tilde{x} \ge \tilde{x}_r - \varepsilon_{\tilde{x}} \tag{18}$$

$$\varepsilon_{\tilde{x}} \geq 0 \tag{19}$$

where $\tilde{x}_r$ is the water safety level and $\varepsilon_{\tilde{x}}$ is the slack to $\tilde{x}_r$.

Stability of MPC is one important issue that has attracted a great deal of attention since local optimization in a finite preview horizon does not guarantee stability in general (Lee *et al.* 1996). The most widely referenced approach to guarantee stability in MPC procedures is to add an equality constraint on the final state in the prediction horizon (a so-called end-state constraint) or put a weight on the final state in the objective function (Thomas 1975; Kwon & Pearson 1977; Kwon & Byun 1989; Mayne & Michalska 1990; Genceli & Nikolaou 1993; De Nicolao & Scattolini 1998). Another approach is to use an infinite prediction horizon with a finite control horizon (Rawlings & Muske 1993), making it possible to apply standard linear quadratic regulator theory to guarantee stability (Kwakernaak & Sivan 1972; Cheng & Krogh 2001). In this paper, additive constraints on the states about the penalty water level in reservoirs is preferred to using a terminal condition in order to avoid infeasibility of the MPC strategies due to uncertainty in the dynamic model. However, it is important to take into account that using a finite state horizon (e.g. 30 days) when the reservoir memory is considerably longer might produce strategies that do not guarantee longer-term stability. This methodological issue will be analysed in future work.

The state space model of the transportation layer is simpler since the states correspond to the tank volumes and the manipulated variables are the flows in pumps and valves. This leads to a standard state space representation (6) for the transportation layer. More details can be found in Ocampo-Martinez *et al.* (2013).

Operational goals

Operational goals for supply layer

The supply network is operated with a 30-day horizon, at daily time interval. The main operational goals to be achieved in the supply network are as follows:

- *Operational safety* (J_{safety}): This criterion refers to maintaining appropriate water storage levels in dams and reservoirs for emergency-handling. Operated in both supply and transportation layers.
- *Demand management* (J_{demand}): This is especially important in the supply layer when urban and irrigation demands exist since urban demands must be fully satisfied while irrigation demands allow some degree of slackness.
- *Balance management* (J_{balance}): This is operated only at supply layer which is necessary for keeping rivers or reservoirs consumed in a balanced way and escaping a water deficit problem for both of the rivers in the longer term.
- *Minimizing waste* (J_{mwaste}): Taking into account that the river water eventually goes to the sea, this avoids unnecessary water release from reservoirs (release water that does not meet any demand and is eventually wasted).
- *Environment conservation* ($J_{\text{ecological}}$): Water sources such as boreholes, reservoirs and rivers are usually subject to operational constraints to maintain water levels and ecological flows.

The above-mentioned goals lead to the following function

$$\begin{aligned} J &= J_{\text{safety}} + J_{\text{demand}} + J_{\text{mwaste}} + J_{\text{balance}} \\ &= \varepsilon_{\tilde{x}}(k)^\top W_{\tilde{x}} \varepsilon_{\tilde{x}}(k) + \varepsilon(k)^\top W_f \varepsilon(k) \\ &\quad + (\tilde{u}_{i\ldots j}(k) - \tilde{u}_s(k))^\top W_{\tilde{w}} (\tilde{u}_{i\ldots j}(k) - \tilde{u}_s(k)) \\ &\quad + \left(\begin{pmatrix} 0\ldots0 & \frac{1}{xi'_{\max}} & 0\ldots0 & \frac{-1}{xj'_{\max}} & 0\ldots0 \end{pmatrix}\tilde{x}(k)\right)^\top w_{\tilde{m}} \\ &\quad \times \left(\begin{pmatrix} 0\ldots0 & \frac{1}{xi'_{\max}} & 0\ldots0 & \frac{-1}{xj'_{\max}} & 0\ldots0 \end{pmatrix}\tilde{x}(k)\right) \end{aligned} \tag{20}$$

where

$$\begin{aligned} \varepsilon_{\tilde{x}}(k) &= \tilde{x}(k) - \tilde{x}_r \\ \tilde{u} &= \Theta\Delta\tilde{u} + \Pi\tilde{u}(k-1) \\ \Delta\tilde{u}(k) &= \tilde{u}(k) - \tilde{u}(k-1) \end{aligned}$$

and

$$\Theta = \begin{pmatrix} I_{m_i} & 0 & \ldots & 0 \\ I_{m_i} & I_{m_i} & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ I_{m_i} & I_{m_i} & \ldots & I_{m_i} \end{pmatrix}, \quad \Pi = \begin{pmatrix} I_{m_i} \\ I_{m_i} \\ \vdots \\ I_{m_i} \end{pmatrix}$$

and $W_{\tilde{x}}$, W_f, $W_{\tilde{w}}$, $W_{\tilde{x}}$, $w_{\tilde{m}}$ are the related weights which decide the priorities (established by the water network authorities) for all the terms appearing in the objective function. The weight tuning method proposed in Toro et al. (2011), based on computing the Pareto front of the multi-objective optimization problem presented in (20), is used in this paper. The initial step of this tuning approach is to find what are known as the anchor points that correspond to the best possible value for each objective obtained by optimizing a single criterion at a time. Then, a normalization procedure is applied, a management point (MP) defined by establishing objective priorities is defined, and the optimal weights are determined by computing those that minimize the distance from the solutions of the Pareto front and the MP.

It should be noted that the term J_{safety} in (20) contains the ecological flows, implicitly including $J_{\text{ecological}}$. The reason is that flows in the rivers are modelled as additional state variables as discussed before. Variables $\tilde{u}_{i\ldots j}(k)$ are the flows from the rivers to the sea, $\tilde{u}_s(k)$ are their ecological penalty levels, and x_i and x_j are two main reservoirs located in two different rivers.

Operational goals for transportation layer

The transportation network is operated with a 24-hour horizon, at hourly time interval. The main operational goals to be achieved in the transportation network are as follows:

- *Cost reduction* (J_{cost}): Water cost is usually related to acquisition, which may have different prices at different sources and elevations, affected by power tariffs which may vary during a day.
- *Operational safety* (J_{safety}): This criterion refers to maintaining appropriate water storage levels in dams and reservoirs of the network for emergency-handling.
- *Control actions smoothness* ($J_{\text{smoothness}}$): The operation of water treatment plants and main valves usually requires smooth flow set-point variations for best process operation.

The above-mentioned goals lead to the following function

$$J = J_{\text{safety}} + J_{\text{smoothness}} + J_{\text{cost}} = \varepsilon_{\tilde{x}}(k)^\top W_{\tilde{x}} \varepsilon_{\tilde{x}}(k) + \Delta\tilde{u}(k)^\top W_{\tilde{u}} \Delta\tilde{u}(k) + W_a(a_1 + a_2(k))\tilde{u}(k) \quad (21)$$

where

$$\begin{aligned} \varepsilon_{\tilde{x}}(k) &= \tilde{x}(k) - \tilde{x}_r \\ \tilde{u} &= \Theta\Delta\tilde{u} + \Pi\tilde{u}(k-1) \\ \Delta\tilde{u}(k) &= \tilde{u}(k) - \tilde{u}(k-1) \end{aligned}$$

and $W_{\tilde{x}}$, $W_{\tilde{u}}$, W_a are the related weights.

The vectors a_1 and a_2 contain the cost of water treatment and pumping, respectively.

Formulation of the optimization problem

The objective function (20) and (21) of the MPC problem can be formulated in the following way:

$$J = z^T \Phi z + \phi^T z + c \quad (22)$$

where

$$z = [\Delta\tilde{u} \quad \varepsilon_{\tilde{x}} \quad \varepsilon]^T \quad (23)$$

and c is a constant value produced by vector calculation.

This allows determination of the optimal control actions at each instant k by solving a quadratic optimization problem by means of QP algorithm in the form

$$\begin{aligned} &\min_z z^\top \Phi x + \phi^\top z \\ &A_1 z \leq b_1 \\ &A_2 z = b_2 \end{aligned}$$

TEMPORAL MULTI-LAYER MPC SCHEME

Multi-layer MPC

There are three basic methods of decomposition of the overall control objective (Brdys & Ulanicki 1994):

- temporal hierarchy,
- spatial hierarchy,
- functional hierarchy.

Among them, temporal hierarchy is particularly important in the control of water systems and it will be presented in the following sections (Brdys & Tatjewski 2005).

The general principle of temporal multi-layer MPC is that the decision of a higher layer has a wider temporal extent than that of a lower layer. At the same time, because of the limited capacity, the higher level decision units process more aggregated information than the lower ones. In this paper, a two-level structure related to the supply and transportation layers of a water network is proposed as shown in Figure 1.

The systems correspond to these two layers and operate according to different goals and time scales. However, both layers use MPC to compute control strategies and controls can be characterized by the pair (H_p, T_s), where H_p is a the time horizon for the optimization problem, T_s is the sampling time.

The operation of the hierarchical structure is presented by Algorithm 1 where the pair (k, m) is used to fix a point on a time scale, with the following meaning: k means the current day, m means the current hour within the current day. K will denote the number of days over which the scheme is in operation and M (which is equal to 24) will be the number of hours in a day. For convenience, the following notation is chosen: $x(k) = x(k, m)$, and x^* to denote the state of the physical system.

Temporal multi-layer coordination techniques

As shown in Figure 1, the way to represent interaction between the upper (daily model for the supply layer) and lower (hourly model for the transportation layer) layers relies on two elements:

- Measured disturbance (M_s): which handles the related aggregated demands at the transportation layer every predictive horizon hour as communication information to the supply layer.
- Target constraint (T_d): which expresses management policies at the supply layer to the transportation layer in the form of control constraints.

Measured disturbance

In the topology of the supply layer, the whole transportation layer is simplified as one aggregated demand. Measured state in every optimization process for supply layer should

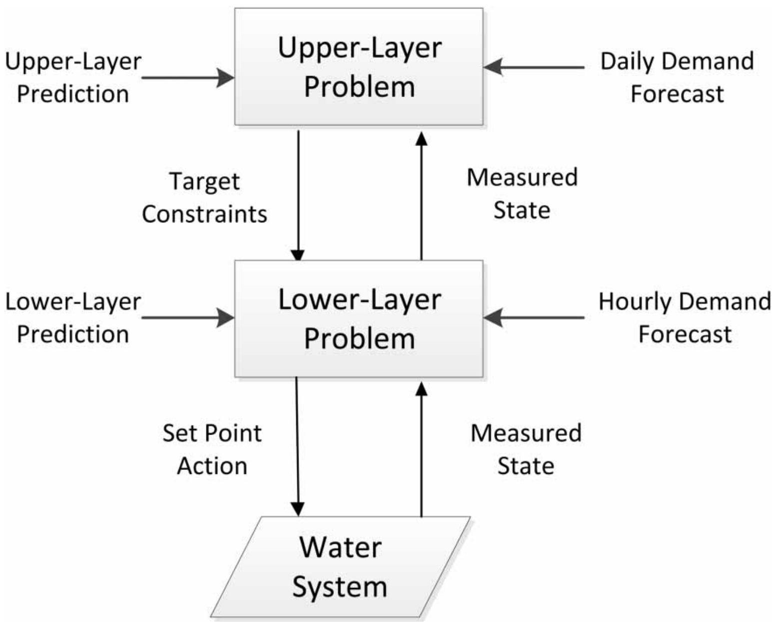

Figure 1 | Temporal hierarchy multi-layer MPC.

Algorithm 1 | Temporal multi-layer MPC

1: **for** $k := 1$ to K**do**
2: initial-state $:= x^*(k)$
3: Predictive horizon := 30 days
4: Control horizon := 30 days
5: model :=model($T_s = 1$ day)
{solve *BOP* to obtain $x(k)$, $x(k+1)$, … send constraints information to lower layer}
6: **for** $m := 1$ to M**do**
7: initial-state $:= x^*(k, m)$
8: Predictive horizon := 24 hours
9: Control horizon := 24 hours
10: model := model($T_s = 1$ hour)
{solve *BOP* to generate a control sequence $u(k, 1)$, $u(k, 2)$, … send aggregated demand to upper layer}
{apply $u(k, 1)$ as set points to a physical system}
{measure the state of the physical system $x^*(k, m+1)$}
11: **end for** {end of $'m'$ loop}
12: **end for** {end of $'k'$ loop};

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be sum of the related demand every prediction horizon (here it is 24 hours)

$$M_s(k) = \sum_{m=1}^{24} d_t(k, m) \tag{24}$$

where $d_t(k, i)$ is demand vector at the transportation layer corresponding to the k-th day.

Thus, $M_s(k)$ should be considered as the demand for the supply layer

$$d_s(k) = M_s(k) \tag{25}$$

Target constraints

The goal for the temporal coordination algorithm is transferring management policies from the upper (supply) to the lower (transportation) layer. In order to achieve this coordination, the following constraint is added to the the lower layer MPC:

$$\sum_{m=1}^{24} u(k, m) \leq T_d(k) \tag{26}$$

where u is the shared control vector between supply and transportation layers.

This constraint is introduced in order to enforce that the amount of water that is decided to be transferred from the supply to the transportation layer by the upper layer MPC is respected by the lower layer MPC. Without such a constraint, the lower layer MPC would decide the amount of water ignoring the upper layer MPC policy.

The coordination working structure is shown in Figure 2.

FORMULATION OF THE TEMPORAL MULTI-LAYER MPC SCHEME

Formulation of temporal coordination problem

As explained in the section 'MPC modelling for supply and transportation layers', the goal for the temporal coordination algorithm is transferring management policies from the upper (supply) to the lower (transportation) layer. In order to achieve this coordination, the constraint (26) is added to the the lower layer MPC. Algorithm 2 shows how this constraint, that establishes a daily limitation, is generated and adapted at every time iteration of the lower layer MPC that operates at an hourly scale. Algorithm 2 takes into account the following facts when generating the constraint (26):

- After the application of n hourly control actions $u_s(m)$ corresponding to the k-th day, the total remaining water for this day will be: $T_d(k) - \sum_{m=1}^{n} u(m)$.

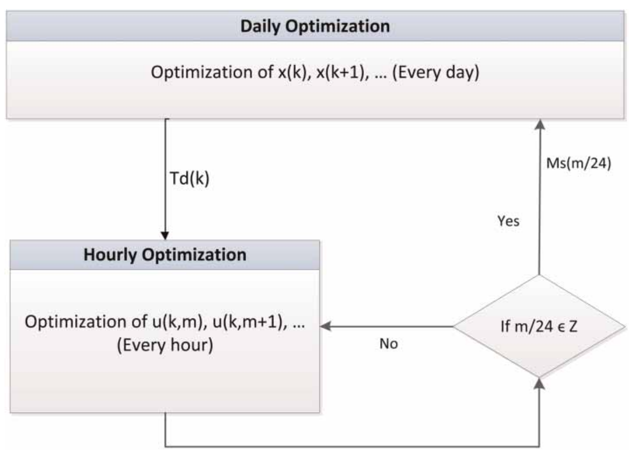

Figure 2 | Upper and lower layer optimizations of multi-layer MPC.

Algorithm 2 | Temporal multi-level coordinator

$L := 24$ hours
$I := 24N$ hours
$T_s := 1$ hour
{start creating new constraints for lower-layer BOP}
for $i := 1$ to I **do**
$d := \text{floor}(i/24)$
$t := \text{rem}(i, 24)$
if $t == 0$ **then**
Update BOP by adding the following constraints:
$u(1|k) \leq T_d(d) - \sum_{j=i-L+1}^{i-1} u_s(j|k)$;
$\sum_{j=2}^{L} u(j|k) \leq T_d(d+1)$;
end if
if $t == 1$ **then**
Update BOP by adding the following constraints:
$\sum_{j=1}^{L} u(j|k) \leq T_d(d+1)$;
end if
if $t == 2$ **then**
Update BOP by adding the following constraints:
$\sum_{j=1}^{L-1} u(j|k) \leq T_d(d+1)$;
$u(L|k) \leq T_d(d+2)$;
end if
if $t \geq 3$ **then**
Update BOP by adding the following constraints:
$\sum_{j=1}^{L-t+1} u(j|k) \leq T_d(d+1) - \sum_{j=i-L+1}^{i-1} u_s(j|k)$;
$\sum_{j=L-t+2}^{L} u(j|k) \leq T_d(d+2)$;
end if
Solve BOP to obtain $u(j|k), u(j+1|k), \ldots$ with the new constraints added
$u_s(i|k) := u(1|k)$;
end for
{end of 'i' loop}

- When limiting the control actions in the prediction horizon L, there is a part of control actions $u(m)$ that corresponds to hours of the current day k that should be limited by $T_d(k)$, while the control actions correspond to hours of the next day $k+1$ that should be limited by $T_d(k) - \sum_{m=1}^{n} u(m)$.
- The generated constraints are added as additional constraints of the BOP problem associated with the lower layer MPC.

Formulation for predicting the water demand

In order to implement the temporal multi-level MPC approach, two demand forecasts algorithms are needed (see Figure 1): one at the daily level and the other at the hourly level. These two algorithms are based on the approach proposed by Quevedo *et al.* (2010):

- A time-series modelling to represent the daily demand forecast.
- A set of different daily flow demand patterns according to the day type to cater for different consumption during the weekends and holiday periods. Every pattern consists of 24 hourly values for each daily pattern (hourly demand forecast).

This algorithm will run in parallel with the MPC algorithms both in supply and transportation layers to obtain the pattern of daily and hourly flow demand.

Daily demand forecast

The daily flow model is built on the basis of a time series modelling approach using an ARIMA strategy. A time series analysis was carried out on several daily aggregate series, which consistently showed a weekly seasonality, as well as the presence of deterministic periodic components. A general expression for the daily flow model, to be used for a number of demands in different locations, was derived using three main components:

- A weekly-period oscillating signal, with zero average value to cater for cyclic deterministic behaviour, implemented using a second-order (two-parameter) model with two oscillating modes

$$\left(p_{1,2} = \cos(2\pi/7) \pm j \sin(2\pi/7)\right)$$

$$\Delta y_{\text{osc}}(k) = \Delta y_{\text{int}} - 2\cos(2\pi/7)\Delta y_{\text{int}}(k-1) + \Delta y_{\text{int}}(k-2)$$

- An integrator takes into account possible trends and the non-zero mean value of the flow data

$$\Delta y_{\text{int}}(k) = y(k) - y(k-1) \tag{27}$$

- An autoregressive component to consider the influence of previous flow values within a week. For the general case, the influence of 4 previous days is considered (28). However, after parameter estimation and significance analysis, the models are usually reduced implementing a smaller number of parameters

$$y(k) = -a_1 y(k-1) - a_2 y(k-2) - a_3 y(k-3) - a_4 y(k-4) \tag{28}$$

Combining the previous components in the following way the structure of aggregate daily flow model for each demand sensor is therefore

$$y_p(k) = -b_1 y(k-1) - b_2 y(k-2) - b_3 y(k-3) - b_4 y(k-4) - b_5 y(k-5) - b_6 y(k-6) - b_7 y(k-7) \tag{29}$$

The parameters $b_1, \ldots, b_7$ should be adjusted using least-squares-based parameter estimation methods and historical data.

Hourly demand forecast

The 1-hour flow model is based on distributing the daily flow prediction provided by the time-series model described in the previous section using a 1-hour flow pattern that takes into account the daily/monthly variation in the following way

$$y_{ph}(k+i) = \frac{y_{\text{pat}}(k, i)}{\sum_{j=1}^{24} y_{pat}(k, j)} y_p(k), \qquad i = 1, \ldots, 24 \tag{30}$$

where $y_p(k)$ is the predicted flow for the current day k using (29) and y_{pat} 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 (for more details see Quevedo *et al.* (2010)).

Handling uncertainty

The main source of uncertainty is related to demands, although some uncertainty in the network dynamics is present as well because of the use of simplified control-oriented models. In this paper, the proposed MPC controller does not handle the uncertainty explicitly. However, because the MPC approach relies on the receding horizon principle, that is based on replanning the control strategy at every iteration, taking into account the measurements collected in real time from telemetry system, uncertainty will be compensated for to a certain extent. To explicitly address the effect of uncertainty in the MPC controller design, robust MPC approaches may be used. These, in general, require representation of uncertainty that may be either deterministic (Lee & Yu 1997; Mayne *et al.* 2000; Chisci *et al.* 2001; Goulart *et al.* 2006; Rakovic *et al.* 2012) or stochastic (Charnes & Cooper 1962; Calafiore & Dabbene 2006; Shapiro *et al.* 2009). The application of those techniques is left as future research in this paper, since the contribution is mainly concentrated in the coordination between MPC controllers operating at different time scales in a regional water network.

CASE STUDY: CATALUNYA REGIONAL WATER NETWORK

Description

The Catalunya Regional Water Network lies within the Catalunya Inland Basins, from which the metropolitan area of Barcelona is fed and where most of the population is concentrated (approximately 5.5 million people). The Catalunya Regional Water Network is composed mainly of two rivers (Llobregat and Ter) and related components. An assessment based on data obtained by the supply companies in the Barcelona metropolitan area shows that in 2007, 81% of the water input came from surface sources. Of the total water input, 90 hm^3 came from the Llobregat system and 124 hm^3 from the Ter system. The water flow supplied by the Ter and Llobregat rivers are regulated by three and two reservoirs and purified by one and two water treatment plants, respectively.

In Figure 3, an aggregate model of Catalunya Regional Water Network is provided. According to the definition of functional decomposition, the Catalunya Regional Water Network can be separated into three layers. The supply

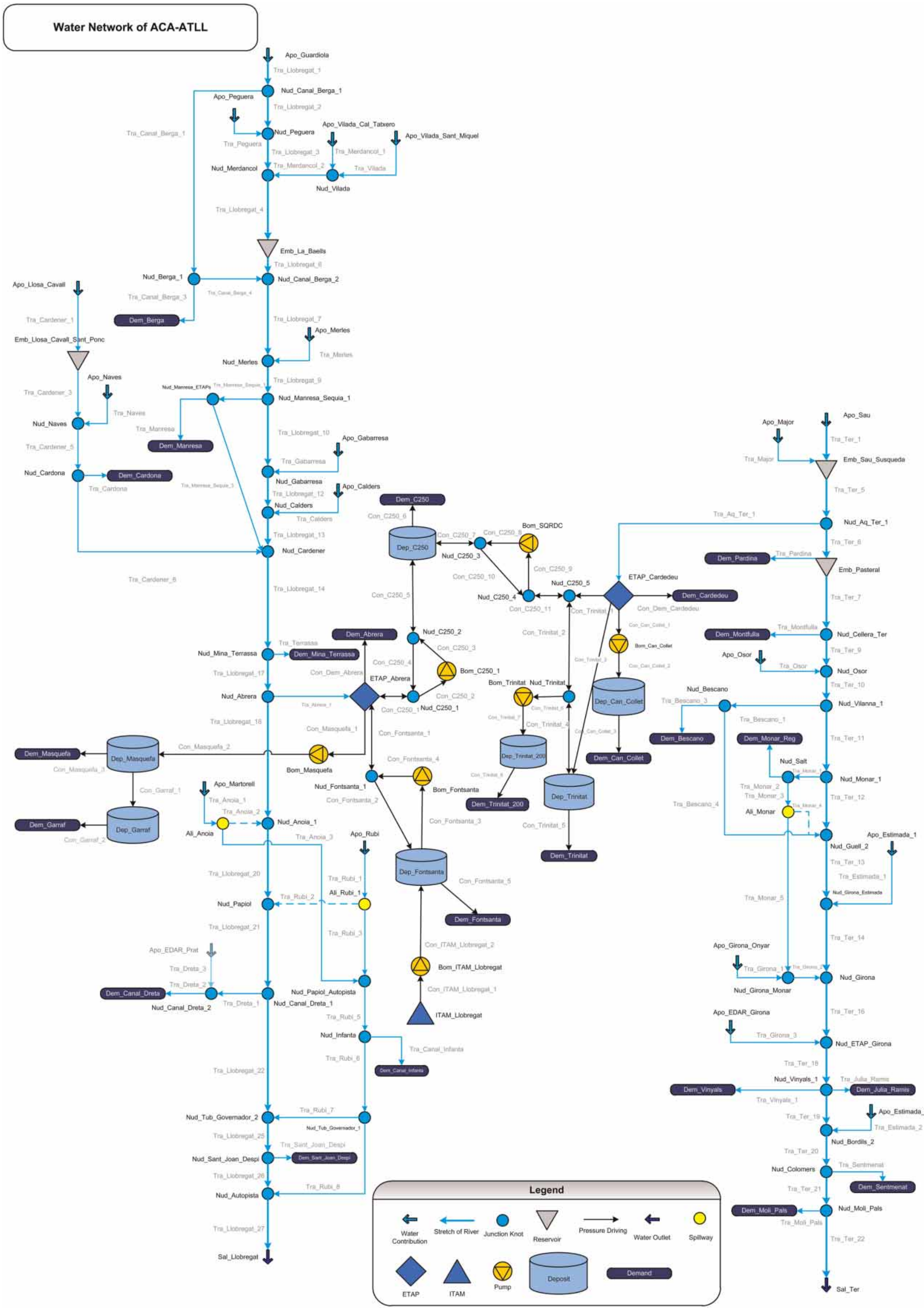

Figure 3 | Aggregate diagram of Catalunya Regional Water Network.

layer is composed of the rivers Llobregat and Ter and all the connected elements, at the two sides of Figure 3. The transportation layer, composed of metropolitan areas and also treatment, desalination plants within them, is in the centre of Figure 3. Demand areas at the transportation layer are represented the distribution layer, which is not described in this network. The hydrological regime of Catalunya is characterized by the irregularity of its rainfall pattern, which, as is typical of the Mediterranean climate, varies greatly between years. This makes the region especially vulnerable to drought episodes, which are expected to increase due to climate change.

Besides that, according to the historical evolution of water reserves evolution in Llobregat and Ter reservoirs, which are the most important reservoirs in the Catalunya Regional Water Network, in the past 30 years (1982–2012), both reservoirs have had more than six water warning problems. What is worse, in the past 20 years (1992–2012), the frequency has increased, as Figure 4 shows. In order to solve this water shortage problem, a desalination plant has been built, which is useful to mitigate the water scarcity; however, the water comes at a large economic and environmental cost which could be quite a large expenditure. Thus, searching for an optimal control technique to meet more efficient use of water resources is quite crucial in such a network. This is the motivation for developing the multi-layer MPC scheme proposed in this paper.

RESULTS

The multi-layer MPC controller presented in the sections 'MPC modelling for supply and transportation layers' and 'Temporal multi-layer MPC scheme' has been implemented using MATLAB and QP solver of TOMLAB. To test the MPC controller in simulation, a simulator of the Catalunya regional network has been developed (see Figure 5).

Supply layer

There are three scenarios according to the amount of water in the different rivers, which are as follows:

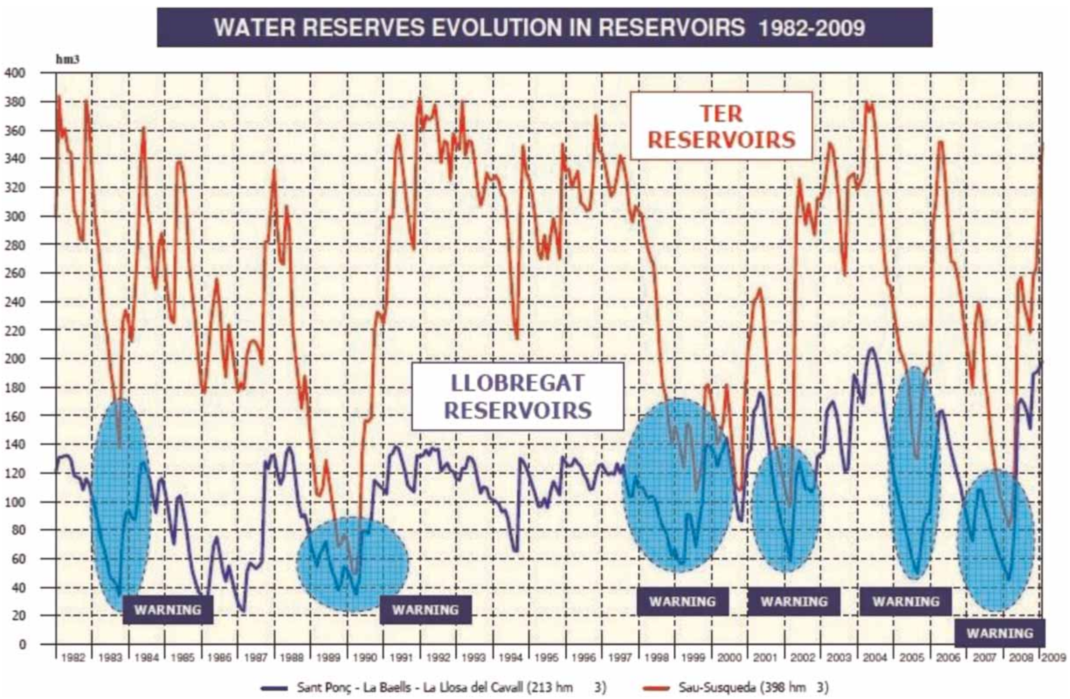

Figure 4 | Urgency problem of Catalunya Regional Water Network.

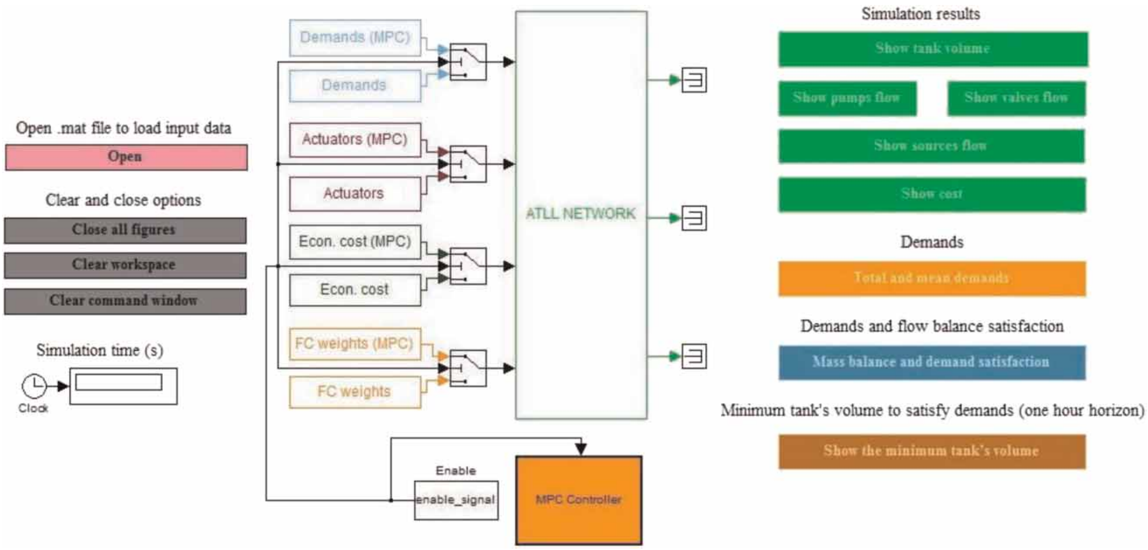

Figure 5 | Simulation of the multi-layer MPC control using MATLAB/SIMULINK.

- *Scenario 1*: More initial water in Llobregat than in Ter.
- *Scenario 2*: More initial water in Ter than in Llobregat.
- *Scenario 3*: Initial water in both rivers are similar.

According to reality use, for the first two scenarios, when water in one river is adequate while in another river it is not, management policies will be set to ask for water from only one of the rivers. For scenario 3, when water is similar in both rivers, according to the balance management, which is one of the control objectives in the supply layer, water consumption in both of the rivers will be proportional to their supplying capacity. Table 1 provides detailed results and also improvement of water usages in the two rivers achieved by this proposed multi-layer MPC scheme. In this table, 'Source' means outside sources flow into rivers, 'Fixed demand' means fixed demands which cannot choose the water source while 'Variable demand' is the demand which can receive water from more than one river. *BD*, abbreviation of 'Balanced demand', is water volume that has been consumed from each of the reservoirs and *PB*, abbreviation of 'Proportion of balanced demand', is the proportion of *BD* for the two reservoirs. *PR*, abbreviation of 'Proportion of reservoir capacity', is the proportion of storage capacities of the two reservoirs. Similar values for *PB* and *PR* is what the multi-layer scheme wants to achieve. *SA*, abbreviation of 'Supplying ability', is water supply ability in days of the whole water network before meeting deficit problems at the hypothesis with no

Table 1 | Balancing comparison of scenario 1

Sc.	Multi-layer MPC control scheme						
Es.	**Source**	**Fixed demand**	**Variable demand**	**BD**	**PB**	**PR**	**SA**
L.	3008	2981	724	697	58.93%	53.48%	242 days
T.	3532	3518	1196	1182			
Sc.	**MPC**						
Es.	**Source**	**Fixed demand**	**Variable demand**	**BD**	**PB**	**PR**	**SA**
L.	3008	2981	7.6	– 19.4	– 1.02%	53.48%	177 days
T.	3532	3518	1914	1900			

rain and no water flow in from outside. The comparisons prove that after using this proposed MPC scheme, the proportion of water usage from the two rivers (58.93%, which is the ratio of Llobregat/Ter) is much closer to the proportion of their storage capacities (53.48%). What is more, the Catalunya Regional Water Network can supply water for 65 days longer than it can without balance management, which is a good benefit for the sustainable usage of water resource in the long-term perspective.

Figure 6 is an example of one river reach. The plot shows that, after ecological control, water flow at this reach could meet the ecological objective during the whole optimization process.

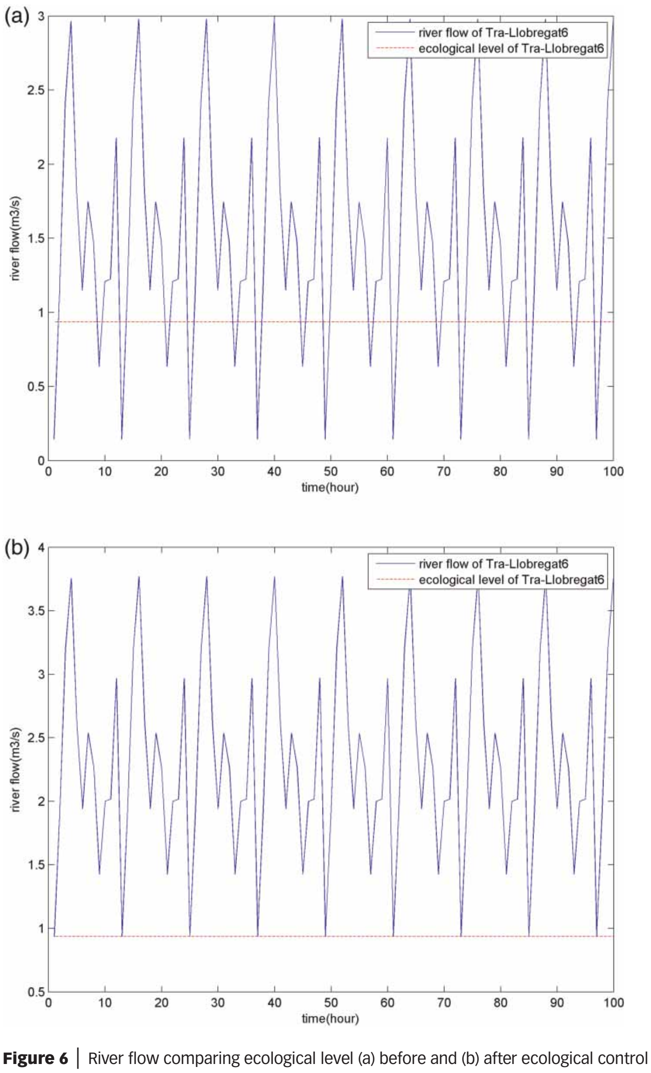

Figure 6 | River flow comparing ecological level (a) before and (b) after ecological control in River Llobregat.

Transportation layer

In the transportation layer, as show in Figure 7, water transportation produces cost when pumping water from a lower elevation to higher elevation. In order to show how electrical cost optimization works, the case of Masquefa reservoir, which is marked using a box in the transportation layer, will be used as an illustrative example. The figure shows that this reservoir is fed by a pump and supplies water for an urban demand corresponding to the city of Masquefa near Barcelona. Figure 8 shows the pump flow and the electricity price. From this figure, it can be seen that the pump sends more water to the reservoir at the lower price period and less or no water at the higher price period. Figure 9 shows, in the same way, the water level in the Masquefa reservoir with electricity price of the pump connected with that reservoir. The water level increases when the connected pump is working corresponding with the night period when the demand is minimal and electricity is cheaper. On the other hand, during the day, the level decreases because consumers start demanding water and pumping is minimized because electricity is expensive. The volume of water that should be stored in the reservoir is determined by the MPC controller taking into account a 24-hour ahead demand forecast.

For the rest of the control objectives in the transportation layer, Figure 10 shows the water level of one tank $\mathrm{Dep_T}$ rinitat comparing its safety level before and after the safety level control.

Coordination

During the coordination process, management policies at the supply layer are transferred to the transportation layer using the method of set-point. Figures 11 and 12 show the amount of water consumed by the transportation layer from the two rivers for satisfying the same demands before and after coordination, respectively. The two figures prove that average levels of water consumption from the two rivers are much closer after balance management.

Table 2 provides detailed numerical results and compares the obtained control results in terms of economic performance over 4 days among the three different control techniques:

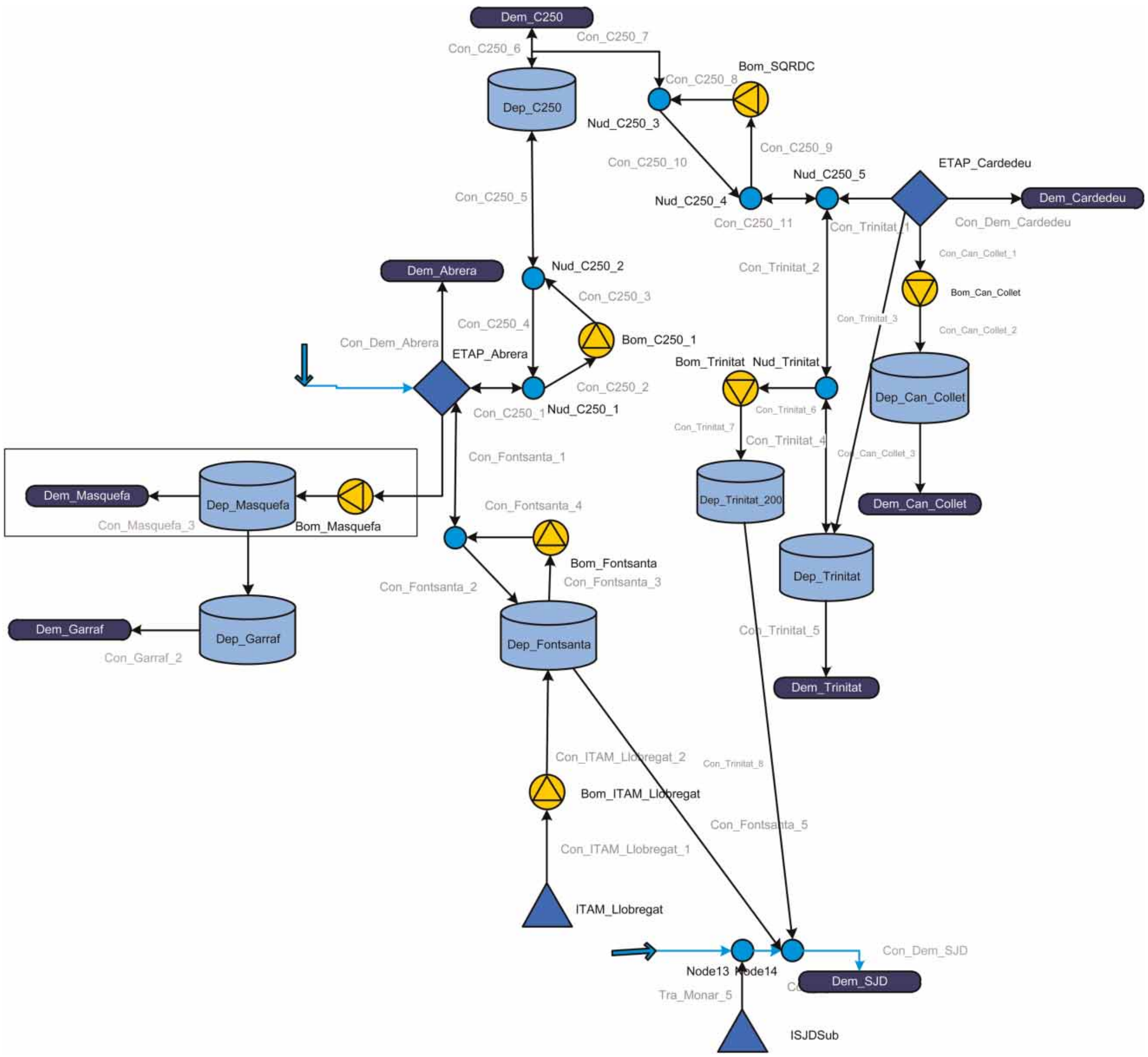

Figure 7 | Transportation network.

- *Current control*: Control the transportation layer of Catalunya Regional Water Network using heuristic strategies by human operators.
- *Multi-layer MPC scheme*: Control the same network using multi-layer MPC techniques with temporal multi-level coordination between the supply and transportation layers.
- *Model predictive control*: Control the transportation layer of Catalunya Regional Water Network using MPC techniques, where no coordination and communication between the supply and transportation layers is used.

In Table 2, Wat., abbreviation of Water, means water cost during the day, while Ele., abbreviation of Electricity, shows electricity cost and Tot., abbreviation of Total, means the total cost which includes both water and electricity. The indices representing costs are given in economic units (e.u.) instead of Euro due to confidentiality restrictions. The row 'Proportion' is the improved proportion to the current control. From this table, the result shows that multi-layer MPC technique with temporal coordination is better than the current control but a little worse than MPC technique without coordination at the point of economic cost, especially of water source cost. The explanation is that while introducing coordination techniques, management policies at the supply layer have also been introduced to the transportation layer. As a consequence, it could

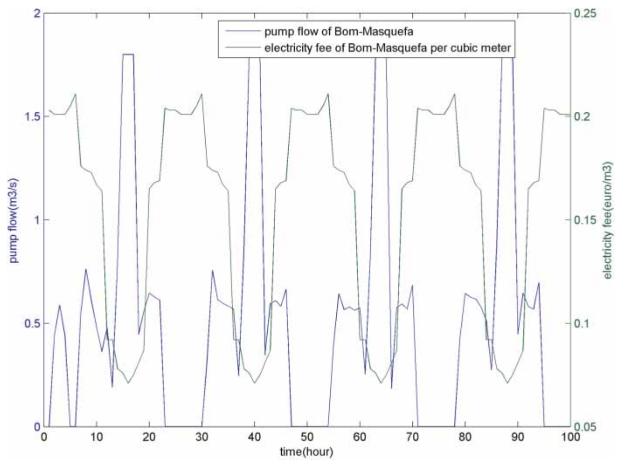

Figure 8 | Pump flow with electricity price.

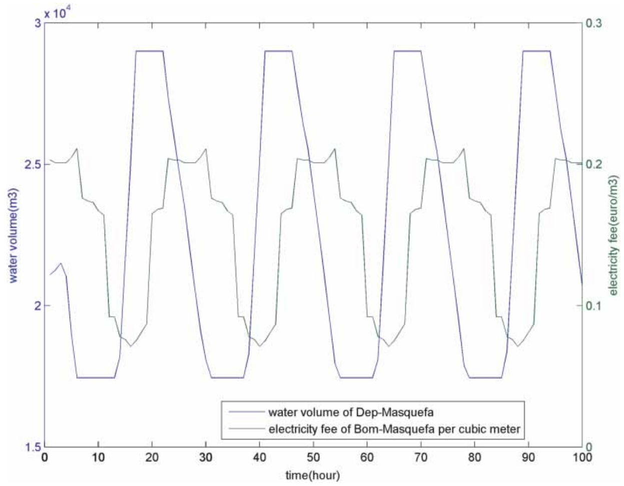

Figure 9 | Water level of Dep Masquefa.

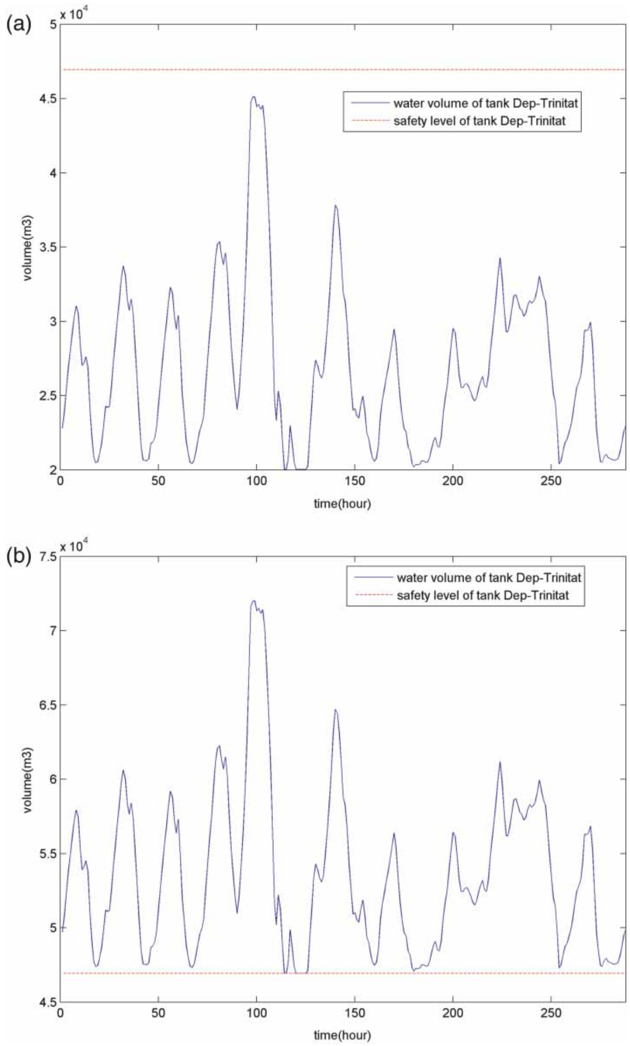

Figure 10 | Water level of tank Dep$_T$ rinitat before and after safety control starts from the date of 01/08/2011.

happen that demands at the transportation layer have to consume less water from the cheaper river while consuming more from the other river which increases the cost. From the long-term perspective, sustainable usage and ecological protection of rivers have been achieved at the price of certain limited cost. As well, even from the economic perspective, the multi-layer MPC with coordination techniques is more feasible than MPC without coordination because the multi-layer MPC can make the Catalunya Regional Water Network supply water for 65 days longer as Table 1 shows, which can save much economic expense for solving the deficit problem.

CONCLUSIONS AND FUTURE WORK

In this paper, a multi-layer MPC scheme with multi-level coordination for regional water supply systems is proposed. The need for a multi-layer scheme derives from the fact that different networks in the water supply and transportation systems are operated according to different management goals, with different time horizons. While the management of the supply network is mainly concerned with long-term safe yield and ecological issues, the transportation layer must achieve economic goals in the short term (hourly strategy), while meeting demands and operational constraints. The use

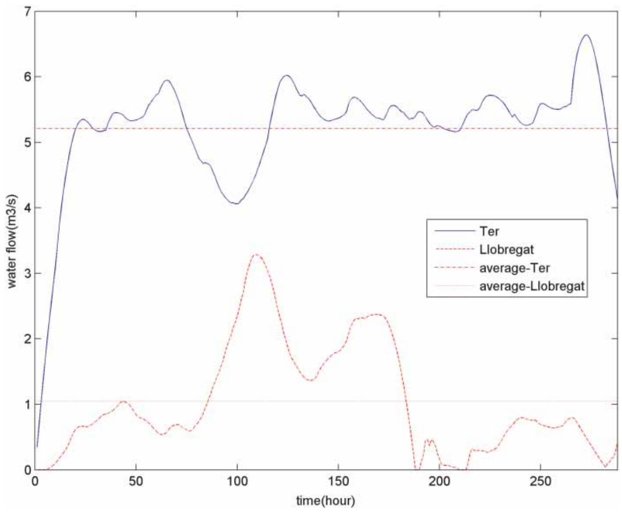

Figure 11 | Flows from the two rivers before using temporal coordination with *x*-time and *y*-flow axis.

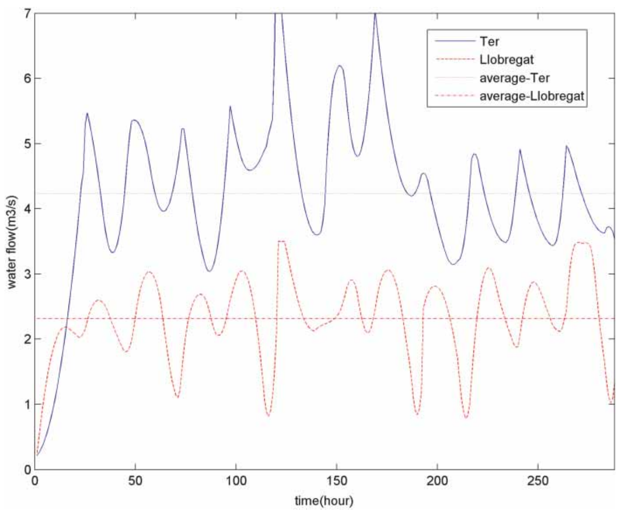

Figure 12 | Flows from the two rivers after using temporal coordination with *x*-time and *y*-flow axis.

of the multi-layer modelling and the temporal hierarchy MPC coordination techniques proposed in this paper make it possible to realize communication and coordination between the two layers in order to let individual operational goals affect each other, and finally, obtain short-term strategies which can effectively consider long-term objectives as well.

According to objective functions, multi-layer MPC is used to generate control strategies for the complete regional water system to meet consumption by daily use or irrigation using optimized economic cost, safety water level in reservoirs, ecological flows in rivers and smooth flow control in actuators. The case study of the Catalunya Regional Water Network has been used to exemplify and verify the proposed management methodology. Results have shown the effectiveness of the proposed modelling and control methodologies allowing a trade-off to be established between short- and long-term goals together that would not be possible if separate controls were applied. This is the main achievement of the proposed scheme.

Uncertainty is handled in an implicit way by the MPC approach by means of the receding horizon philosophy that replans the control strategy after each iteration considering the measurements provided by the water network telemetry system. The explicit handling of uncertainties may be addressed using robust MPC techniques, and this will be addressed as future research.

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

	Current control			Multi-layer MPC			MPC		
Day	**Wat.**	**Ele.**	**Tot.**	**Wat.**	**Ele.**	**Tot.**	**Wat.**	**Ele.**	**Tot.**
11/08/02	240	100	340	213	44	257	141	40	181
11/08/03	239	106	345	237	47	284	170	39	209
11/08/04	246	94	340	238	48	286	171	41	212
11/08/05	264	110	374	253	66	319	168	42	210
Proportion				– 5%	– 50%	– 18%	– 34%	– 61%	– 42%

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REFERENCES

Brdys, M. & Ulanicki, B. 1994 *Operational Control of Water Systems: Structures, Algorithms and Applications*. Prentice Hall International, New York.

Brdys, M. A. & Tatjewski, P. 2005 *Iterative Algorithms for Multilayer Optimizing Control*. Imperial College Press, London.

Brdys, M. A., Grochowski, M., Gminski, T., Konarczak, K. & Drewa, M. 2008 Hierarchical predictive control of integrated wastewater treatment systems. *Control Eng. Pract.* **16**, 751–767.

Calafiore, G. & Dabbene, F. 2006 *Probabilistic and Randomized Methods for Ddesign under Uncertainty*. Springer, Dordrecht.

Cembrano, G., Quevedo, J., Salamero, M., Puig, V., Figueras, J. & Martí, J. 2004 Optimal control of urban drainage systems: a case study. *Control Eng. Pract.* **12**, 1–9.

Cembrano, G., Quevedo, J., Puig, V., Perez, R., Figueras, J., Ramon, G., Rodryguez, P., Barnet, G., Casas, M., Verdejo, J. M., Gil, A., Marti, J. & Konig, H. 2005 First results of predictive control application on water supply and distribution in Santiago, Chile. 16th IFAC World Congress, pp. 25–30.

Charnes, A. & Cooper, W. 1962 Chance constraints and normal deviates. *J. Am. Stat. Assoc.* **57**, 134–148.

Cheng, X. & Krogh, B. H. 2001 Stability-constrained model predictive control. *IEEE Trans. Automat. Contr.* **46**, 1816–1820.

Chisci, L., Falugi, P. & Zappa, G. 2001 Predictive control for constrained systems with polytopic uncertainty. *Proc. Amer. Contr. Conf.* **4**, 3073–3078.

De Nicolao, L. M. & Scattolini, R. 1998 Stabilizing receding-horizon control of nonlinear time-varying systems. *IEEE Trans. Automat. Contr.* **43**, 1030–1036.

Evans, R., Li, L., Mareels, I., Okello, N., Pham, M., Qiu, W. & Saleem, S. K. 2011 Real-time optimal control of river basin networks. Preprints of the 18th IFAC World Congress, pp. 11459–11464.

Genceli, H. & Nikolaou, M. 1993 Robust stability analysis of constrained norm model predictive control. *AIChE J.* **39**, 1954–1965.

Goulart, P. J., Kerrigan, E. C. & Maciejowski, J. M. 2006 Optimization over state feedback policies for robust control with constraints. *Automatica* **42**, 523–533.

Kwakernaak, H. & Sivan, R. 1972 *Linear Optimal Control Systems*. Wiley, New York.

Kwon, W. H. & Pearson, A. E. 1977 A modified quadratic cost problem and feedback stabilization of a linear system. *IEEE Trans. Automat. Contr.* **AC-22**, 838–842.

Kwon, W. H. & Byun, D. G. 1989 Receding horizon tracking control as a predictive control and its stability properties. *Int. J. Control* **50**, 1807–1824.

Lee, J. & Yu, Z. 1997 Worse-case formulations of model predictive control for systems with bounded parameters. *Automatica* **33**, 763–781.

Lee, T., Wang, Q. & Tan, K. 1996 Robust Smith-predictor controller for uncertain delay systems. *AIChE J.* **42** (4), 1033–1040. Available at: http://onlinelibrary.wiley.com/doi/10.1002/aic.690420415/pdf.

Litrico, X. & Fromion, V. 2004 Simplified modeling of irrigation canals for controller design. *J. Irrig. Drain. Eng.* **130**, 373–383.

Maciejowski, J. M. 2002 *Predictive Control with Constraints*. Prentice Hall, Harlow, UK.

Marinaki, M. & Papageorgiou, M. 2005 *Optimal Real-time Control of Sewer Networks*. Springer, London.

Mayne, D. & Michalska, H. 1990 Receding horizon control of nonlinear systems. *IEEE Trans. Automat. Contr.* **35**, 814–824.

Mayne, D., Rawlings, J., Rao, C. & Scokaert, P. 2000 Constrained model predictive control: Stability and optimality. *Automatica* **36**, 789–814.

Mays, L. 2004 *Urban Stormwater Management Tools*. McGraw-Hill Professional Publishing, New York.

Negenborn, R. R. 2008 *Multi-Agent Model Predictive Control with Applications to Power Networks*. Delft University Press, Delft, The Netherlands.

Ocampo-Martinez, C., Puig, V., Cembrano, G. & Quevedo, J. 2013 Application of predictive control strategies to the management of complex networks in the urban water cycle. *IEEE Control Syst. Mag.* **33**, 15–45.

Overloop, P. J. V. 2006 *Model Predictive Control on Open Water Systems*. Delft University Press, Delft, The Netherlands.

Quevedo, J., Puig, V., Cembrano, G. & Blanch, J. 2010 Validation and reconstruction of flow meter data in the Barcelona water distribution network. *Control Eng. Pract.* **11**, 640–651.

Rakovic, S., Kouvaritakis, B., Cannon, M., Panos, C. & Findeisen, R. 2012 Parameterized tube model predictive control. *IEEE Trans. Automat. Contr.* **57**, 2746–2761.

Rawlings, J. B. & Muske, K. R. 1993 Stability of constrained receding horizon control. *IEEE Trans. Automat. Contr.* **38**, 1512–1516.

Scattolini, R. 2009 Architectures for distributed and hierarchical model predictive control: A review. *J. Process Control* **19**, 723–731.

Shapiro, A., Dentcheva, D. & Ruszczynski, A. 2009 *Lectures on Stochastic Programming: Modeling and Theory*. Society for Industrial and Applied Mathematics and Mathematical Programming Society, USA.

Tatjewski, P. 2008 Advanced control and on-line process optimization in multilayer structures. *Annu. Rev. Control* **32**, 71–85.

Thomas, Y. A. 1975 Linear quadratic optimal estimation and control with receding horizon. *Electron. Lett.* **11**, 19–21.

Toro, R., Ocampo-Martinez, C., Logist, F., Impe, J. V. & Puig, V. 2011 Tuning of predictive controllers for drinking water networked systems. *Proc. 18th IFAC World Congress*, 28 August–2 September, Milan, Italy.

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