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Improving water management efficiency by using optimal control strategies: the Barcelona case study

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Abstract: This paper describes preliminary results of applying model-based predictive control (MPC) techniques for flow management in a large-scale drinking water networks including a telemetry/telecontrol system. MPC technique is used to generate flow control strategies from the sources to the consumer areas to meet future demands with appropriate pressure levels, optimizing performance indexes associated to operational goals such as network safety volumes and flow control stability. The designed management strategies are applied over real case study based on a representative model of the drinking water network of Barcelona (Spain).

Keywords: optimal control; predictive control; large-scale systems; drinking water systems.

INTRODUCTION

Drinking water management in urban areas is a subject of increasing concern as cities grow. Limited water supplies, conservation and sustainability policies, as well as the infrastructure complexity for meeting consumer demands with appropriate flow, pressure and quality levels make water management a challenging control problem. Decision support systems provide useful guidance for operators in complex networks, where resources management best actions are not intuitive. Optimization and optimal control techniques provide an important contribution to a smart management strategy computation for drinking water networks (DWN), see [1], [2], [3]. Similarly, problems related to modelling and control of water supply, transport and distribution systems have been object of important research efforts during the last few years (see, e.g., [4], [5], [6]).

This paper describes preliminary results of a collaborative project between AGBAR, the company in charge of water transport and distribution in Barcelona and its metropolitan area (Spain), and the Advanced Control Systems research group (SAC) from the Technical University of Catalonia (UPC). The objective of the project consists in applying model-based predictive control (MPC) techniques for flow management in a large-scale water transport system. This is a pressurized water transport network comprised by multiple tanks, pumping stations, water sources (superficial and underground) and sectors of demand. The MPC technique is used here to generate flow-control strategies from the drinking water treatment plants to the consumer areas to meet future demands, optimizing a performance index expressing operational goals such as cost, water safety storage and flow control stability. The main contribution of this paper consists in highlighting the advantages of using optimal control to improve the performance of a DWN. The proposed techniques are tested over the water transport network of Barcelona, a representative example of a large-scale and complex DWN.

The structure of the paper is the following: First, modelling and optimal/predictive control of DWNs is revised. Then, the description of the case study based on an aggregated model of the Barcelona drinking water system is presented. Next, the main results obtained from simulations of the closed-loop system using optimal/predictive control techniques are discussed. Different aspects and issues of the simulations are commented on. Finally, the main conclusions are given closing the paper.

MODELLING FOR OPTIMAL/PREDICTIVE CONTROL OF DWNs

A convenient description of the model of a DWN may be obtained by considering the set of flows through the actuator elements as a vector of control variables, the set of tanks volumes as a vector of observable state variables and, since the model is used for predictive control, a set of flows of demands as a disturbance vector of demand forecasts, obtained through appropriate prediction models. In order to obtain the DWN model, the following elements and basic relations are introduced.

The mass balance expression relating the stored volume in tanks, *x(k)*, the manipulated tank inflows and outflows, *u(k)*, and the demands can be written as the difference equation

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

where $q_{\text{in},i}(k)$ and $q_{\text{out},j}(k)$ correspond to the *i*-th tank inflow and the *j*-th tank outflow, respectively, given in m^3/s. The physical constraint related to the range of tank volume capacities is expressed as

$$x^{min} \le x(k) \le x^{max}, \tag{2}$$

where $x^{\min}$ and $x^{\max}$ denote the minimum and the maximum volume capacity, respectively, given in m^3. As this constraint is physical, it is impossible to send more water to a tank than it can store.

Within a DWN, nodes correspond to intersections of mains. The static equation that expresses the mass conservation, can be written as

$$\sum_i q_{\text{in},i}(k) = \sum_j q_{\text{out},j}(k), \tag{3}$$

where $q_{\text{in},i}(k)$ and $q_{\text{out},j}(k)$ correspond to the *i*-th node inflow and the *j*-th node outflow, respectively, given in m^3/s . Therefore, considering the expressions presented above, the model used for this study has the following discrete-time representation in state space:

$$x(k+1) = Ax(k) + Bu(k) + B_p d(k), \tag{4}$$

where $x(k) \in \mathbb{R}^n$ is the state vector corresponding to the water volumes of the tanks, $u(k) \in \mathbb{R}^m$ represents the vector of manipulated flows through the actuators, $d(k) \in \mathbb{R}^p$ corresponds to the vector of disturbance predictions which, in this case, are the water demands. A, B, B_p and C are the system matrices of suitable dimensions and k is the discrete time instant. Since the demands are supposed to be known, *d(k)* is a known vector containing the measured disturbances affecting the system. Therefore, (4) can be rewritten as

$$x(k+1) = Ax(k) + \tilde{B}\tilde{u}(k), \tag{5}$$

where $\tilde{B} = [B \quad B_p]$ and $\tilde{u}(k) = [u(k)^T \quad d(k)^T]^T$. Regarding the system constraints and according to the network modelling, they are related to:

- Mass balance relations at the network nodes (relations between manipulated inputs and, in some cases, measured disturbances). These are equality relations of the form

$$E_1 \tilde{u}(k) = E_2 . \tag{6}$$

- Bounds in system states and measured inputs expressed by (2) and the inequality

$$u^{min} \leq u(k) \leq u^{max} , \tag{7}$$

where u^{min} and u^{max} are vectors with the lower and upper limits of the actuator, respectively.

Hence, expressions in (2), (5), (6) and (7) constitute the set of constraints related to DWN modelling.

OPTIMAL/PREDICTIVE CONTROL OF DWNs

Along the last few years, MPC has shown to be one of the most effective and accepted control strategies for complex systems [7]. The objective of using this technique for controlling DWNs is to compute, in a predictive way, the best manipulated inputs in order to achieve the optimal performance of the network according to a given set of control objectives and predefined performance indexes. MPC strategies have some important features to deal with complex systems as water networks such as the inclusion of disturbance (demand) prediction, use of physical constraints, relatively simple to work with, multivariable systems handling. So, according to [8], such controllers are very suitable to be used in the global control of networks related to the urban water cycle within a hierarchical control structure, where the MPC controller determines the references for the local controllers located on different elements of the network. There is also a management level that is used to provide the MPC controller with the operational objectives, which are reflected in the controller design as the performance indexes to be minimized.

Control Objectives and Cost Function

This paper considers that a MPC design should satisfy the operational objectives described below according to a given order of priority.

Water production and transport cost. The economical costs associated to drinking water production are due to: chemicals, legal canons and electricity costs. Moreover, the transport of this drinking water through the overall water network plays an important role as for electricity costs in pumping stations. For this study, this control objective can be described by the expression

$$f_1(k) = W_\alpha \left(\alpha \, u(k) \right) + W_\gamma \left(\gamma(k) \, u(k) \right), \tag{8}$$

where α corresponds to a known vector related to the economical costs of the water according to the selected source (treatment plant, dwell, etc.) and $\gamma(k)$ is a vector of suitable dimensions associated to the economical cost of the flow through certain actuators (pumps only) and their control cost (pumping). The super-index 1 denotes the linear nature of the term. Note the k-dependence of γ since the pumping effort has different values according to the moment of the day (electricity costs). Weight matrices W_α and W_γ penalize the control objective related to the economical costs in the optimization process.

Safety storage term. The satisfaction of water demands should be fulfilled at any time instant. This is guaranteed through the equality constraints of the water mass balances at demand sectors. However, some infeasibility avoidance mechanisms should be introduced in the management of the tank volumes so that this volume does not go below a safety limit for future availability. This leads to the management of the tank volumes above a certain safety volume, which ensures that the demand flows can always be supplied by the network. Preliminary approaches to this control objective within a quadratic framework suggest an expression of the form

$$f_2(k) = \begin{cases} 0 & \text{if } x(k) \geq \beta \\ \left(x(k)-\beta\right)^T W_x \left(x(k)-\beta\right) & \text{if } x(k) < \beta \end{cases}, \tag{9}$$

where β is a term which determines the security volume to be considered for the control law computation.

Stability of control actions. Pumps and valves should operate smoothly in order to avoid big transients in the pressurized pipes that can lead to their damage. Similarly water flows requested from treatment plants must have a smooth profile because of the plants operational constraints. To obtain such smoothing effect, the MPC controller includes in the objective function a third term that penalizes control signal variation $\Delta u(k) = u(k) - u(k-1)$. This term be expressed as

$$f_3(k) = \Delta u(k)^T W_u \Delta u(k), \tag{10}$$

where $\Delta u(k)$ corresponds to the vector of changes of the inputs and W_u corresponds to the weight matrix of suitable dimensions. Therefore, the performance function $J(k)$, considering the aforementioned control objectives has the form

$$J(k) = \sum_{i=0}^{H_u-1} f_1(k+i) + \sum_{i=1}^{H_p} f_2(k+i) + \sum_{i=0}^{H_u-1} f_3(k+i), \tag{11}$$

where H_p and H_u correspond to the prediction and control horizons, respectively. In this equation, index k represents the current time instant while index i represents the time along the prediction and control horizons.

DEMAND FORECASTING

The demand forecasting used for the MPC controller procedure consists of two levels:

- a time-series modelling to represent the daily aggregated flow values and
- a set of daily flow demand patterns different according to the day type to cater for different consumption during the week-ends and holidays periods. Every pattern consists of 24 hourly values for each daily pattern.

The daily series of hourly flow predictions is computed as a product of the daily aggregated flow value and the appropriate hourly demand pattern.

Aggregated daily flow model. The aggregated daily flow model is built on the basis of a time series modelling approach using ARIMA strategy. A time series analysis was carried out on several daily aggregated series, which consistently showed a weekly seasonality, as well as the presence of deterministic periodic components. Deterministic cyclic behaviour in a time series is detected by the cancellation of operators in the autoregressive end the moving average parts of the model. A general expression for the aggregate 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 in s-plane: $s_{1-2}=\pm\ 2\pi/7\ j$ (or equivalently, in z-plane: $z_{1-2}= e^{s_{1-2}} = cos(2\pi/7) \pm sin(2\pi/7)j$). Then, the oscillating polynomial is:

$$y(k)= 2cos(2\pi /7)y(k-1)- y(k-2) \tag{12}$$

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

$$y(t)= y(k-1) \tag{13}$$

- *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. However, after parameter estimation and significance analysis, the models are usually reduced to a smaller number of parameters

$$y(k)=-a_1 y(k-1)- a_2 y(k-2)- a_3 y(k-3)- a_4 y(k-4) \tag{14}$$

Combining the three components (12)-(14) in the following way:

$$\Delta y_{\text{int}}(k) = y(k) - y(k-1),$$
$$\Delta y_{osc}(k) = \Delta y_{\text{int}}(k) - 2\cos(2\pi/7)\Delta y_{\text{int}}(k-1) + \Delta y_{\text{int}}(k-2),$$
$$y_p(k) = -a_1\Delta y_{osc}(k-1) - a_2\Delta y_{osc}(k-2) - a_3\Delta y_{osc}(k-3) - a_4\Delta y_{osc}(k-4),$$

the structure of aggregate daily flow model for each sensor is then:

$$y_p(k)=-b_1y(k-1)-b_2y(k-2)-b_3y(k-3)-b_4y(k-4)-b_5y(k-5)-b_6y(k-6)-b_7y(k-7) \tag{15}$$

The parameters of this model should be adjusted using parameter estimation methods (as for example, the least-square methods.) and historical data free of faults.

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

$$y_{p1h}(k+i)=\frac{y_{pat}(k,i)}{\sum_{j=1}^{24} y_{pat}(k,i)}y_p(j) \quad i=1,\cdots,24 \tag{16}$$

where $y_p(k)$ is the predicted flow for the current day j using (15) and $y_{pat}(k,i)$ is the prediction provided by the one hour-flow pattern with the flow pattern class day/month of the actual day.

CASE-STUDY DESCRIPTION

The water transport network of Barcelona will be used as a case study in this paper. This network covers a territorial extension of 425 km^2, with a total length of 4470 km. Every year it supplies 237,7 hm^3 of drinking water to a population of more than 2,8 millions of inhabitants. The network has a centralized telecontrol system, organized in a two-level architecture. At the upper level, a supervisory control system installed in the control centre of AGBAR is in charge of controlling the whole network by taking into account operational constraints and consumer demands. This upper level provides the set points for the lower-level control system. On the other hand, the lower level optimizes the pressure profile to minimize losses by leakage and to provide sufficient pressure, e.g., for high-rise buildings.

Simplifying Assumptions

This paper considers an *aggregated* version, which is a representative version of the entire network of Barcelona. Aggregated means that some demand sectors of the network are concentrated in a single point. Similarly, some tanks are aggregated in a single element and the respective actuators in a single pumping station or valve. Pumping stations flows are treated as continuous variables. This means that a pumping station is modelled as being able to produce any flow in a certain range, so that the problem of individual pump scheduling to produce the desired flow is required to operate single pumps (not treated here). The aggregated network, depicted in Figure 1, is comprised of 17 tanks (state variables of the dynamical network model), 61 actuators (model control variables divided in 26 pumping stations and 35 valves), 11 nodes and 25 main sectors of water demand (model disturbances). The detailed information about physical parameters and other system values is reported in [9].

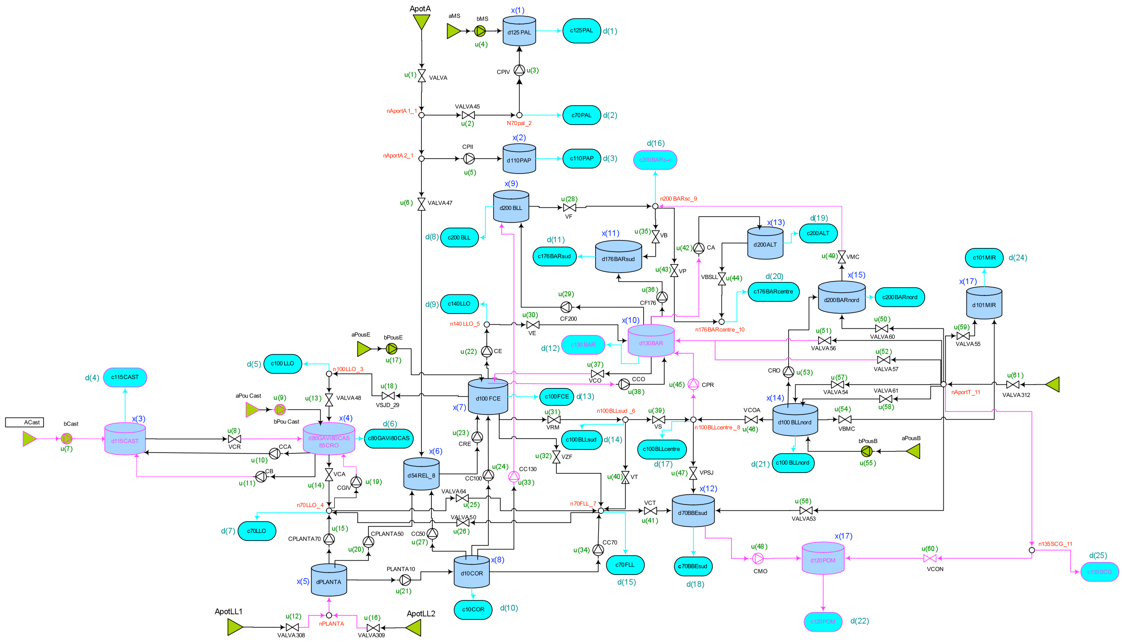


Figure 1. Barcelona drinking water network: aggregate case study.

SIMULATIONS AND RESULTS

Simulator of Barcelona DWN

A toolbox for simulation of DWN has been developed in MATLAB/SIMULINK, which allows implementing simulators of DWNs. The results presented in this section were tested against a simulator developed using this DWN simulation toolbox. Figure 2 presents the SIMULINK block diagram of the simulator. This simulator not only allows to test the MPC controller developed in closed-loop but also to evaluate the real operating economic cost of the control strategies developed using such a controller. Using this simulator, it is possible to compare the economic cost of the manual operation of the network against the optimized one using the MPC controller.

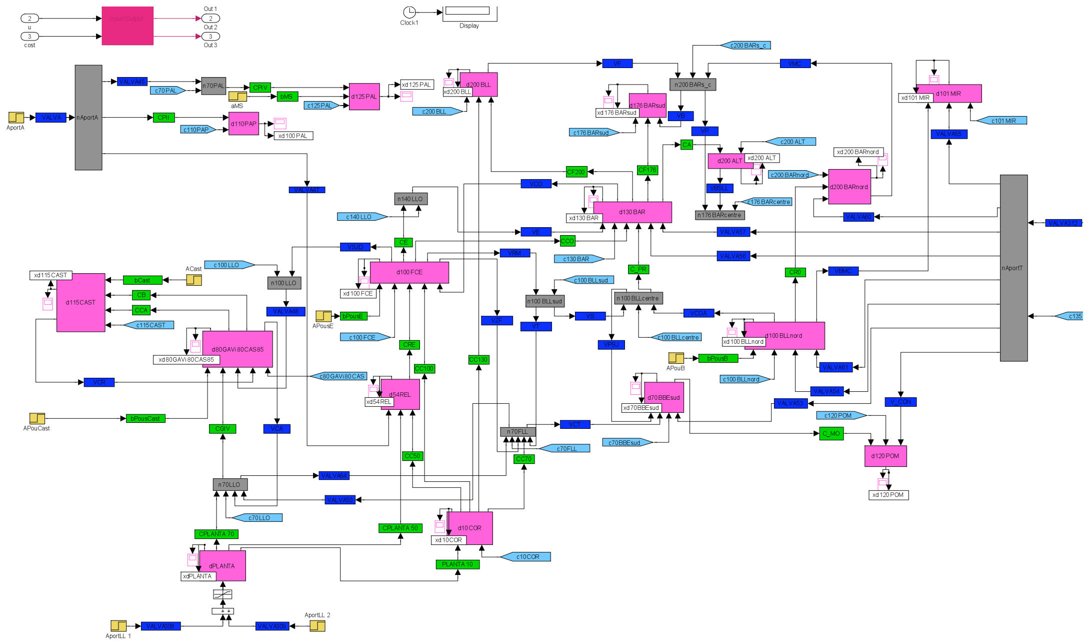


Figure 2. Simulator of Barcelona drinking water network

Tuning Set-up of the MPC controller

The MPC controller developed for the optimal control of the Barcelona network uses a prediction horizon of 24 hours. The demand forecast uses de procedure described in demand forecast section of this paper. The safety volumes of tanks have been determined increasing by a 20% the volumes required to satisfy the demand an hour ahead. The MPC performance function, as discussed in the MPC section, includes three terms: economical cost, safety and stability terms. The main objective is to minimize cost. At the same time, safety and stability objectives must be optimized. The relative importance of these objectives is given by the weight in the performance function. Table 1 presents the results of the tuning procedure where just one weight is emphasised at time. Numbers are not given in real economical units due to confidential reasons. The controller also takes advantage of the electrical cost tables so that the optimal strategy can be found trying to pump when electricity is less expensive (in Barcelona mainly during the night time).

Table 1. Tuning set-up of the MPC controller

Priority	Economical Cost	Water Cost	Electricity Cost
Economical cost	68.63	59.24	9.39
Security	130.93	117.84	13.09
Trade-off	70.49	61.98	8.52

Closed-loop Results

The case study was implemented using the real data (demands, operational ranges of elements, etc.). Figure 3 shows a demand profile corresponding to the 24-hour demand distribution in one demand sector. Similar demand patterns are used on all demand locations. The test considers a periods of 3 consecutive days.

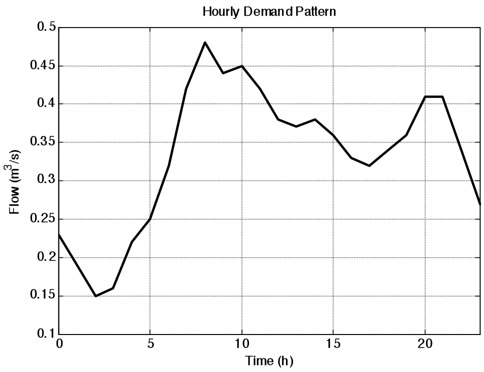
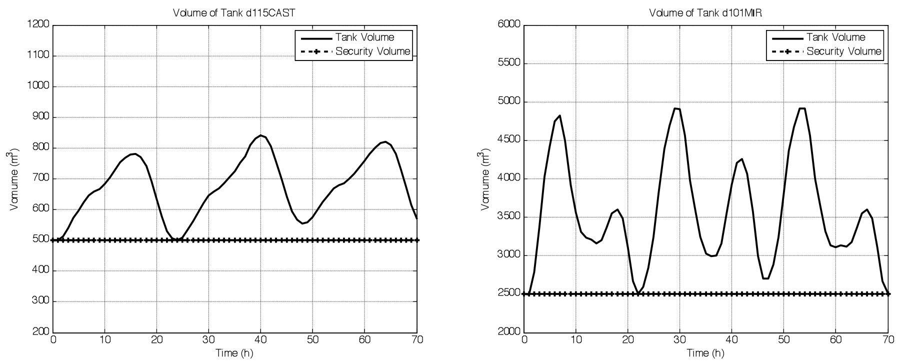


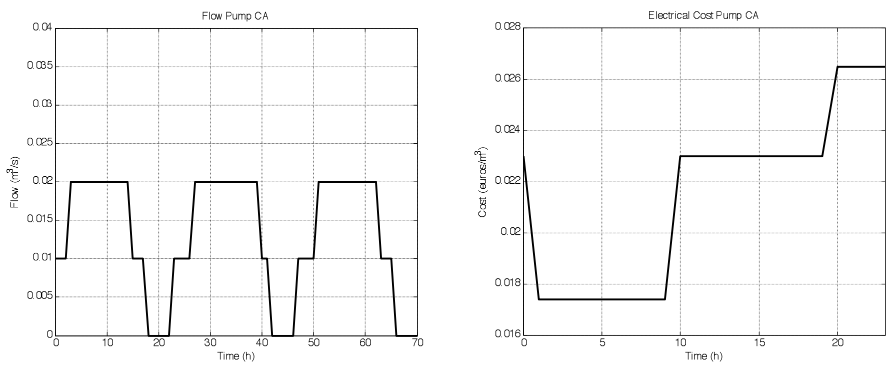
Figure 4. Hourly pattern of a demand sector

Figure 5(a) and 5(b) plot the evolution of two tanks of Barcelona network during 72 hours. This figure shows that the demand may be efficiently satisfied and the safety volume is maintained at all times. Figure 6(a) shows the flow pumped to the tank d115CAST whose volume evolution is presented in Figure 5(b). It can be noticed that MPC controller decides to avoid pumping at the peak electricity tariff times (see Figure 6(b)). In Figure 5(b), the volume evolution of tank d101MIR shows that, in order to supply water for the latter part of the day, it is necessary to receive water during the day in addition to filling tank at night time with low electricity tariff (see Figure 6(b)). It is important to note that the application allows for emptying the tank close to the safety limit, so as to avoid pumping during peak-tariff time. In Figures 7(a) and 7(b), the total flow required from two treatment plants is presented. These show how the stability term in the cost function has efficiently handled the storage capability of the network to satisfy the demands with stable flows from the plants.



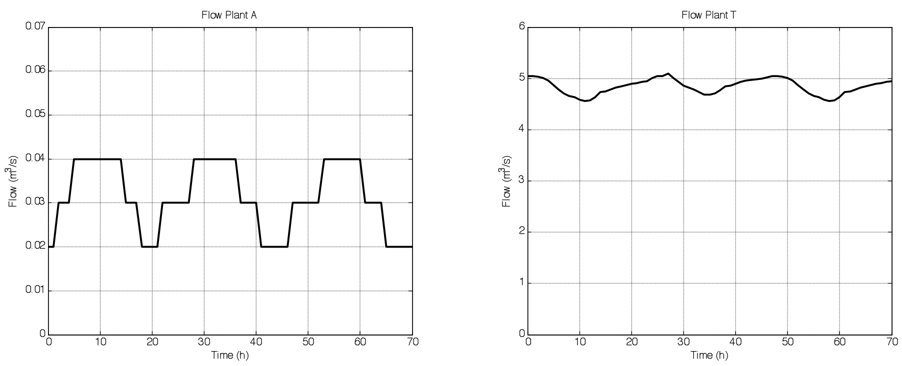
(a) (b)

Figure 5. Volume evolution of two selected tanks



(a) (b)

Figure 6. Pumped flow to the tank d115CAST and electrical cost tariff for this pump



(a) (b)

Figure 7. Outflow from water treatment plants

CONCLUSIONS AND FURTHER WORK

This paper has presented preliminary results of applying MPC techniques for flow management in a large-scale drinking water network including a telemetry/telecontrol system. The obtained results have shown the smart capabilities of MPC to generate control strategies that fulfil the tanks to appropriate to meet demand, reducing water transport and production costs by taking into account time-varying electrical tariffs and by using less expensive sources while maintaining the safety tank volumes for avoiding risk of water supply. Moreover, the use of a stability term in the performance function to be optimized by the MPC strategy provides smooth flows from the treatment plants. This fact implies an efficient handling of the plants, avoiding performance problems of these elements. The next step of this study, currently underway, is to compare the optimal strategies computed by the MPC control with the current strategies applied in the real system by AGBAR in order to compare costs and the degree of completion of the safety and stability goals.

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