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Operational Predictive Optimal Control of Barcelona Water Transport Network

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Abstract: This paper describes the application of model-based predictive control (MPC) techniques to the supervisory flow management in large-scale drinking water networks including a telemetry/telecontrol system. MPC technique is used to generate flow control strategies (set-points for the regulatory controllers) from the sources to the consumer areas to meet future demands, optimizing performance indexes associated to operational goals such as economic cost, network safety volumes and flow control stability. The designed management strategies are applied to a model of a real case study: the drinking water transport network of Barcelona (Spain).

Keywords: Model predictive control, water supply, optimal control, demand forecast.

1. 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, water quality and service 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 (Westphal *et. al*., 2003), (Nitivattananon *et al*., 1996), (Tu *et al*. 2005). 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., (Brdys and Ulanicki, 1994) (Cembrano *et al*., 2000) (Maksimovic *et al*., 2003) (Butler and Memon, 2006)).

In general, DWNs contain multiple tanks, pumping stations, valves, water sources (superficial and underground) and sectors of consumer demand (Brdys and Ulanicki, 1994). The MPC technique is used here to generate flow-control strategies (set-points for the regulatory controllers) from the drinking water treatment plants to the consumer areas to meet future demands, optimizing a performance index expressing operational goals such as economic cost, water safety storage and flow control stability. The main contribution of this paper consists in highlighting the advantages of using optimization-based control techniques as MPC to improve the performance of a DWN taking into account the added complexity of the MPC design for these systems, namely, their large scale (in terms of number of dynamic elements and decision variables), the nature of the desired control objectives and the type and behaviour of the system disturbances (drinking water demands). The developed control strategies have been tested on the drinking water transport network of Barcelona, a representative example of a model of a large-scale and complex DWN.

This paper describes the results of SOSTAQUA, 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 is to apply model-based predictive control techniques for flow management in large-scale water transport systems.

The structure of the paper is the following: In *Section 2,* the operational control of water networks is reviewed*. Section 3* presents the control oriented modelling approach used for the different network elements as well as the methodology used for demand forecasting. *Section 4* presents the implementation details of the predictive optimal strategy. *Section 5* shows the application of the optimal operative control of the Barcelona water network using several selected real scenarios in simulation. Conclusions and on-going work are outlined in *Section 6*.

2. OPERATIONAL CONTROL OF WATER NETWORKS

2.1 Operational control of water networks

In most water networks, the operational control is managed by the operators from the telecontrol centre using a SCADA (Supervisory Control And Data Acquisition) system. They are in charge of supervising the network status using the telemetry system and setting the set-points for the local controllers. The main goal of the operational control of water networks is to meet the demands at consumer sites, but at the same time with minimum costs of operation and guaranteeing pre-established volumes in reservoirs (to preserve the satisfaction of future demands) and stable operation of actuators (valves and pumps) and production plants.

Water consumption in urban areas is usually managed on a daily basis, because reasonably good hourly 24-hour-ahead demand predictions may, in general, be available and common transport delay times between the supplies and the consumer sites allow operators to follow daily water request patterns. Therefore, this horizon is appropriate for evaluating the effects of different control strategies on the water network, with respect to operational goals. However, other horizons may be more appropriate in specific utilities. The approach in this work is based on demand management at the transport and distribution levels, taking into account the supply conditions. For illustration, it uses -but is not restricted to- a 24-hour horizon, with hourly sampling. When applied in real time conditions, the computation of optimal strategies is updated, with new data from the water network, every hour with a sliding 24-hour horizon (Brdys and Ulanicki 1994).

At the supply level, strategic planning deals with sustainable use of the water resources, seasonal variations in reservoirs and water levels, etc., so that planning horizons and sampling times are usually much longer. In this work, the long-term planning objectives for the supplies are taken into account as bands of admissible requests from the supplies to the transport, production and distribution areas. These admissible bands define bounds on flow from reservoir, aquifer, and river sources. Production plant limitations are also used and these may vary according to weather-related factors, operational schedules and/or breakdowns. The computation of optimal strategies must take into account the dynamics of the complete water system and 24-hour-ahead demand forecasts, availability predictions in supply reservoirs and aquifers, defined by long-term planning for sustainable use and predictions of production plant capacity and availability. Moreover, the telemetry system and operational database will provide the current state of the water system.

2.2 Operational control of water network using model predictive control

Water networks are very complex multivariable systems. In order to improve their performance, model predictive control (MPC) (Camacho and Bordons, 2004; Maciejowski, 2002) provides suitable techniques to implement the operational control of water systems since it allows to compute optimal control strategies *ahead in time* for all the flow and pressure control elements of a water system. Moreover, MPC allows taking into account physical and operational constraints, the multivariable and MIMO nature, demand forecasting requirement, and complex multi-objective operational goals of water networks. The optimal strategies are computed by optimizing a mathematical function describing the operational goals in a given time horizon and using a representative model of the network dynamics, as well as demand forecasts. As discussed in (Marinaki and Papageorgiou, 2005) (Ocampo-Martínez, 2007) (Brdys *et al.*, 2008), among others, MPC is very suitable to be used in the global control of networks related to the urban water cycle within a hierarchical control structure. This global control structure is shown in Figure 1, where the MPC determines the references for the local controllers located on different elements of the network. The *management level* is used to provide MPC with the operational objective, which is reflected in the controller design as the performance indexes to be optimized.

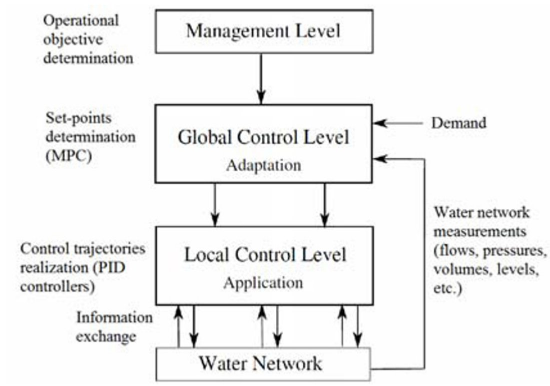

Fig. 1. Hierarchical control structure used in for the operational control of water networks

3. NETWORK AND DEMAND MODELLING FOR OPERATIONAL OPTIMAL CONTROL

3.1 Network model

The control oriented model of a water network allows predicting the effect of control actions on all the network elements. For the purpose of MPC control, a large number of control actions must be tested and evaluated during the optimization process. Therefore, it is important to develop mathematical models to be:

- Representative of the hydraulic dynamic response.
- Simple enough to allow for a large number of evaluations in a limited period of time, imposed by real-time operation.

Following this spirit, the next subsection shows a summary of the modelling methodology used.

3.1.1 Network model and variables

A water system will generally contain a number of flow- or pressure-control elements, located at the supplies, at the water treatment plant inlets or within the network, and controlled through the telecontrol system. A convenient description of the dynamic model of a water network is obtained by considering the set of flows through these n_u control elements (valves and pumps) as the vector of control variables $u \in \Re^{n_u}$. The state of the network, or the effect of control actions, may be observed in passive elements, such as water storage tanks. Then, the set of n_x tank volumes monitored through the telemetry system is a vector of state variables $x \in \Re^{n_x}$. Water demand at consumer nodes may be considered a stochastic disturbance in the model. Then, $d \in \Re^{n_d}$ is a vector of stochastic disturbances containing the values of the demands at the n_d consumer nodes in the network. Since the model is used for predictive control, d will generally be a vector of demand forecasts, obtained through appropriate demand prediction models

The dynamic model of the network may then be written, in discrete time, as:

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

This expression describes the effect on the network, at time $k+1$, produced by a certain control action u, at time k, when the network state was described by $x(k)$. Function f represents the mass and energy balance in the water network and k denotes the instantaneous values at sampling time k, $d(k)$ is the demand prediction at time k and $\theta(k)$ are the parameters of the network at time k.

3.1.2 Elementary models of the network elements

In order to obtain the DWN control-oriented model, the constitutive elements and basic relationships are introduced.

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

$$x_i(k+1) = x_i(k) + \Delta t\left(\sum_i q_{in,i}(k) - \sum_j q_{out,j}(k)\right) \tag{2}$$

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

$$x^{\min} \leq x \leq x^{\max} \tag{3}$$

where x^{min} and x^{max} denote the minimum and the maximum volume capacity, respectively, given in m^3. Since this is a physical limit, it is expressed as a hard constraint: it is impossible to send more water to a tank than it can store. In addition to this physical limit a security level in tanks is considered as a soft constraint to avoid risk situations and possible infeasible solutions.

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

$$\sum_i q_{in,i}(k) = \sum_j q_{out,j}(k) \tag{4}$$

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 control-oriented model of a DWN in discrete-time state space may be written as:

$$x(k+1) = Ax(k) + Bu(k) + B_p d(k) \tag{5}$$

where $x \in \mathbb{R}^n$ is the state vector corresponding to the water volumes of the tanks at time k, $u \in \mathbb{R}^m$ represents the vector of manipulated flows through the actuators, and $d \in \mathbb{R}^p$ corresponds to the vector of demands. A, B, and B_p are the system matrices of suitable dimensions. Since the demands can be forecasted and they are assumed to be known, d is a known vector containing the measured disturbances affecting the system. Therefore, (5) can be rewritten as

$$x(k+1) = Ax(k) + \tilde{B}\tilde{u}(k) \tag{6}$$

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

- Mass balance relationships at the network nodes (relations between manipulated inputs and, in some cases, measured disturbances). These equalities are written as

$$E_1\tilde{u}(k) = E_2 \tag{7}$$

- Bounds on system states (3) and measured inputs expressed by and the inequality

$$u^{\min} \leq u \leq u^{\max} \tag{8}$$

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

Hence, expressions in (3), (6), (7) and (8) constitute the set of constraints related to the DWN mathematical model.

3.2 Model for predicting the water demand

The demand forecasting algorithm used by the tool that implements the MPC control consists of two levels:

- A time-series modelling to represent the daily aggregate flow values, and
- 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 daily pattern consists of 24 hourly values..

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. Demand patterns are obtained from statistical analysis. For more details see (Quevedo, 2010).

4. MPC CONTROL OF WATER TRANSPORT SYSTEMS

4.1 Operational goals

The immediate control goal of a water supply system is to meet the demands at consumer sites according to users' needs. Predictive control techniques may be used to compute strategies which achieve this, while also optimizing the system performance in terms of different operational criteria, such as:

- *Water production and transport cost reduction*. The main economic costs associated to drinking water are due to production (water cost) and delivering though the network (electricity cost). The separately evaluation of water and electrical costs allows the study of their effects on the optimal solution. For this study, this control objective can be described by the expression

$$J_1(k) = W_\alpha(\alpha u(k)) + W_\gamma(\gamma(k)u(k)) \tag{12}$$

where α corresponds to a known vector related to the economic costs of the water according to the selected source (treatment plant, well, etc.) and $\gamma(k)$ 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 γ since the pumping effort has different values according to the time of the day (electricity costs). Weight matrices W_α and W_γ penalize the control objective related to economic 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 risk prevention mechanisms should be introduced in the tank management so that, additionally, the stored volume is preferably maintained over safety limit for eventual emergency needs and to guarantee future availability. A quadratic expression for this concept is used, as follows:

$$J_2(k) = \begin{cases} 0 & if \quad x(k) \geq \beta \\ (x(k)-\beta)^T W_x (x(k)-\beta) & if \quad x(k) \leq \beta \end{cases} \tag{13}$$

where β is a term which determines the security volume to be considered for the control law computation and matrix W_x defines the weight of the objective in the cost function.

- *Set-point stability for equipment conservation*: The operation of water treatment plants and main valves and pumps usually requires smooth flow set-point variations. To obtain such smoothing effect, the proposed MPC controller includes a third term in the objective function to penalize control signal variation between consecutive time intervals, i.e., this term is expressed as

$$J_3(k) = \Delta u(k)^T W_u \Delta u(k) \tag{14}$$

Therefore, the performance function *J(k),* considering the aforementioned control objectives has the form

$$J = \sum_{k=0}^{H_p-1} J_1(k) + \sum_{k=1}^{H_p} J_2(k) + \sum_{k=0}^{H_p-1} J_3(k) \tag{15}$$

where H_p corresponds to the prediction horizon. In this equation, index k represents the current time instant.

The highest priority objective is the economic cost, which should be minimized while obtaining acceptable satisfaction of security and stability objectives. Further improvements in objective priority handling can be obtained by using a lexicographic approach as suggested in (Ocampo-Martínez *et al.*, 2008). Although water quality is not included in this study it could be added as a term in the objective function of the proposed MPC controller.

The strategy computation is based on a mathematical model of network dynamics and its operational goals, as well as on demand prediction. The network dynamics model must compute network response to a control action; the mathematical expression of the operational goal evaluates different candidate control sequences over the 24-hour period and an optimization procedure selects the best one.

4.2 Control strategy computation

The control strategy computation is based on the implementation on a receding horizon control strategy as in MPC using *Algorithm 1* that poses and solves an optimal control problem at each time k (Camacho and Bordons, 2004).

$$\min_{\tilde{u}_k} J(\tilde{x}_k, \tilde{u}_k, \tilde{d}_k) \tag{16}$$

subject to:

$$\begin{cases} x(k|j+1) = f(x(k|j), u(k|j), d(k|j), \theta(k)) \\ u(k|j) \in \mathbb{U} \quad j = 0, \cdots, H_p - 1 \\ x(k|j) \in \mathbb{X} \quad j = 1, \cdots, H_p \end{cases}$$

where:

$$\mathbb{U} = \left\{ u \in \mathbb{R}^m \middle| u_{min} \leq u \leq u_{min} \right\}$$

$$\mathbb{X} = \left\{ x \in \mathbb{R}^n \middle| x_{min} \leq x \leq x_{min} \right\}$$

and

$$\tilde{u}_k = \left(u(k|j) \right)_{j=0}^{H_{p-1}} = \left(u(k|0), u(k|1), \cdots, u(k|H_{p-1}) \right)$$

$$\tilde{x}_k = \left(x(k|j) \right)_{j=1}^{H_p} = \left(x(k|1), x(k|2), \cdots, x(k|H_p) \right)$$

$$\tilde{d}_k = \left(d(k|j) \right)_{j=0}^{H_{p-1}} = \left(d(k|0), d(k|1), \cdots, d(k|H_{p-1}) \right)$$

According to this algorithm, at each time step, a control input sequence $\tilde{u}_k$ of present and future values is computed to optimize the performance function $J(\tilde{x}_k, \tilde{u}_k, \tilde{d}_k)$, according to a prediction of the system dynamics over the horizon H_p. This prediction is performed using demand forecasts and the network model. However, only the first control input $u_{k|0}$ is actually applied to the system, until another sequence based on more recent data is computed. The same procedure is restarted at time *k+1*, using the new measurements obtained from sensors and the new model parameters obtained from the recursive parameter estimation algorithm that is working in parallel. Feedback from the telemetry system is used, and the optimal control strategy is re-computed at each time *k*.

The control input sequence optimizes the performance index $J(\tilde{x},\tilde{u},\tilde{d})$ described in *Section 4.1* over the optimization horizon, in general, of the order of 24h subject to a set of constraints, namely the network dynamics, the demand forecast and de feasibility constraints, i.e. the limits on the state variables, such as minimum and maximum tank volumes, all described in section 3.

Algorithm 1. MPC Algorithm

$k=0$
loop
$x(k|0) \leftarrow$ EstimateStates($y(k)$)
$\theta(k) \leftarrow$ EstimateParameters($y(k)$)
$\tilde{d}_k = \left(d(k|0), d(k|1), \cdots, d(k|H_{p-1})\right) \leftarrow$ EstimateDemands($d(k)$)
$\tilde{u}_k = \left(u(k|0), u(k|1), \cdots, u(k|H_{p-1})\right) \leftarrow$ Solve Optimal Control Problem (16)
Apply control action $u(k|0)$
$k=k+1$
end loop

5. APPLICATION: THE BARCELONA WATER TRANSPORT NETWORK

As application case study to show the performance of the used tool to implement the MPC control, some results of its application off-line (in simulation) in several real scenarios are presented.

5.1 Network description

The Barcelona water network supplies water to approximately 3 million consumers, distributed in 23 municipalities in a 424 km^2 area. Water can be taken from both surface and underground sources. The most important ones in terms of capacity and use are Ter, which is a surface source, and Llobregat, which water can be taken from one surface source and one underground source. From sources water is supplied to 218 demand sectors through around 4645 km of pipe. The complete transport network has been modelled using: 63 storage tanks, 3 surface sources and 6 underground sources, 79 pumps, 50 valves, 18 nodes and 88 demands. The network is controlled through a SCADA system (Figure 2) with sampling periods of 1 hour. For the predictive control scheme a prediction horizon of 24 h is chosen. This record is updated at each time interval.

Fig. 2. Barcelona Water Network control scheme

In Figure 3 the whole network representation using elements of the modelling and optimal control tool used is shown. Sources are represented using a triangle. The main ones are highlighted with a circle. It is a simplified model of the real system. Demand elements contains inside another network (distribution network), which is basically make up of connection to all users. Pumps and valves are simplified too. In general each actuator can integrate several pumps or valves working in parallel.

5.2 Network operational objectives

According to the requirements established by Aigües de Barcelona (AGBAR), the company responsible of the management of the water network described, the operational objectives described in section 4.1 should be satisfied.

These objectives can be easily handled with the tool used. In particular, the first objective is satisfied through the inclusion in the optimization model of appropriate constraints associated to demand elements. Each actuator has associated two operational limits as a minimum and maximum flow, so the second objective is satisfied too, while the other three objectives are combined in a multi-objective function as discussed in *Section 4*.

5.3 Test scenarios

To test and adjust the MPC controller implemented some different scenarios have been chosen. The main difference between scenarios studied is related to sources operation. So, the objective of this study is not only to show the potential of the tool used, but also the comparison with current control strategy and the effects of sources' management in the electrical and water costs.

With reference to sources' management two different scenarios are shown: scheduled flow and flow optimization.

Both scenarios have been calibrated to ensure that results are going to be comparable with current control strategy, (i.e. initial and security volumes according to real data). Objective function weights are adjusted by changing its values in different optimisations and studying the effects on results.

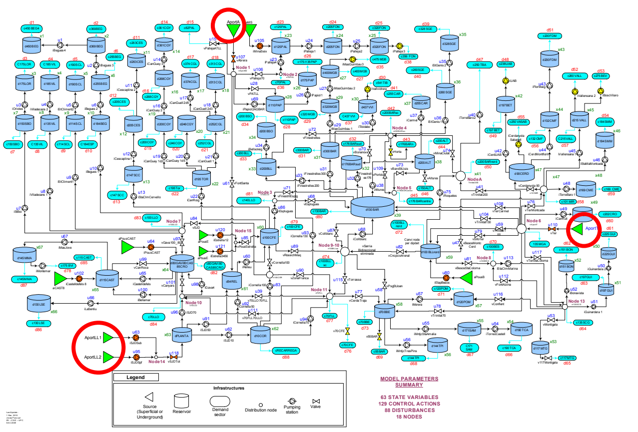

Fig. 3. Barcelona water network description

The period of both scenarios is of 96 hours (4 days), and all of them correspond to the period between July 23 and July 26 of 2007. It means that the demand is the same in both scenarios, so they are comparable. To estimate the demand of each sector the demand forecast method presented in Section 3.2 is used. The volume of demand for each day is shown in Table 1. It is obtained from the total sources' contribution.

Table 1. Total input volume for studied days

Day	1	2	3	4	Mean
Input volume (m3)	633.694	668.136	617.744	627.406	636.745
Mean flow (m3/s)	7,334	7,733	7,150	7,262	7,370

5.4 Results

In all test scenarios, the optimisation tool obtained control solutions to meet demands and operational constraints at all times, while optimizing the operational goals. Some illustrative results of the predictive control application on the complete Barcelona supply network are presented in the following section. For these tests the same model is used, implemented using Matlab.

5.4.1 Scenario 1: Scheduled flow

In this first scenario, sources flow is imposed using real data obtained from AGBAR historical database. The interesting point of this scenario is the comparison between MPC control and current control strategy: water sources management is the same in both cases. This case of study is going to show the potential of the optimisation tool as regards the possible reduction of the electrical cost.

Sources flow evolution is shown in Figure 4. As it can be seen in this scenario Llobregat and Ter sources' supply in average a flow of 7 m^3/s, while Abrera and underground sources mean contribution is about 1 m^3/s.

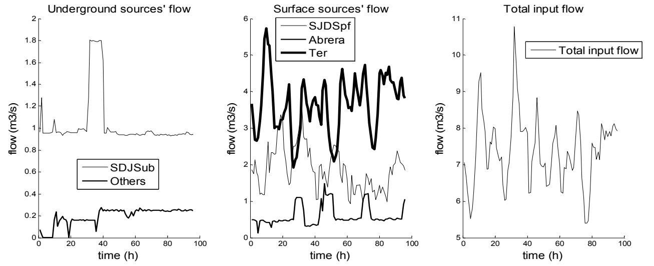

Fig. 4. Sources flow evolution for scenario 1: scheduled flow.

In Table 2 the Scheduled flow scenario costs are compared with those obtained from the current control strategy. Differences are represented as an increase or decrease % with regard to the current control strategy.

Table 2. Current control strategy costs versus Scheduled flow scenario costs comparison

Day	Current control costs (in %)			Scheduled flow costs' improvement (in %)		
	Electrical	Water	Total	Electrical	Water	Total
1	33,13	66,87	100,00	-23,27	+0,00	-7,71
2	34,66	65,34	100,00	-10,56	+0,00	-3,66
3	32,00	68,00	100,00	-20,61	+0,00	-6,59
4	31,29	68,71	100,00	-18,58	+0,00	-5,81

Water cost represents a value near 70 % of the total cost, and there is no variation of this cost in the MPC control because of the fixed sources. With regard to electrical cost the improvement is between 10 and 25 %, which represents a decrease of the total cost between 3 and 8 %.

To show the differences between the current control and the MPC control, some tank volume and actuators flow graphics are shown. In Figure 5 some tank volume evolution can be seen, as well as maximum and security volumes.

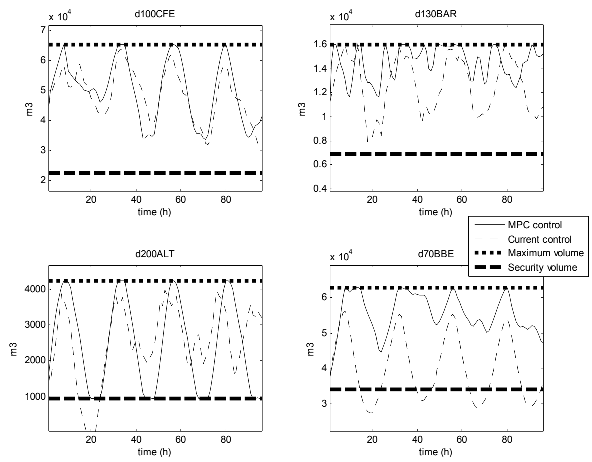

Fig. 5. Some tanks volume evolution: current control and MPC control comparison.

Below, in Figure 6 the effects of the stability term in the objective function are shown. As it can be seen in pumps 1 and 2, the signal with stability term is clearly smoother, while in the third one no differences are appreciated.

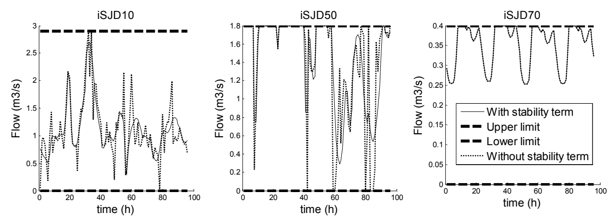

Fig. 6. Stability term effects on pumping operation

The stability term is not the only factor with effects on pumps operation. The electrical fee for each pump is another factor that affects pumps operation in order to minimise electrical cost. In Figure 7 the effects of the electrical fee are shown. It can be seen that if it is possible, pumps only run during the cheapest period (e.g. pump iPalleja1). In cases where with a maximum flow during off-peak hours the necessary volume is not reached, pumps must work during other periods. Pump *iFnestrelles200* is an example of this case. Since it is not enough to pump during the cheapest period, this pump is pumping during the medium cost period too, but with a maximum flow lower than in the cheapest one.

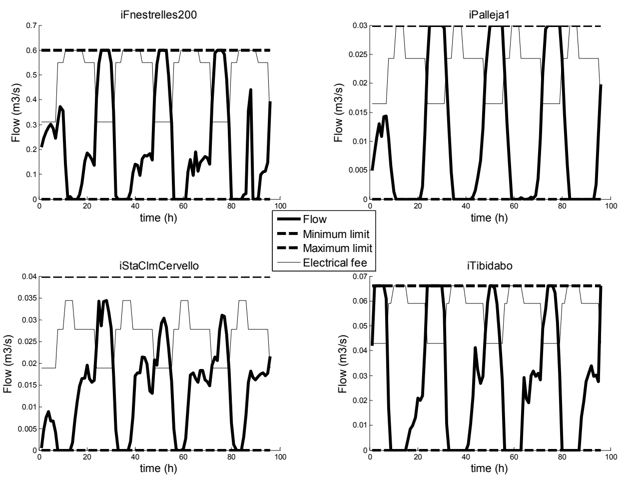

Fig. 7. Electrical fee effects on pumps operation

5.4.2 Scenario 2: Flow optimization

In this second scenario, sources flow is optimised. It means that the only limitation is the minimum and the maximum flow of actuators in the output of each source. In this case both electrical and water cost are optimised, so it is expected to get a higher improvement in the total cost referring to the scenario 1, where sources flow was fixed. This scenario represents a theoretical solution of the water management in the Barcelona water transport network. Indeed, the optimization carried out gives total freedom to the different sources, whilst on a real situation sources are not unlimited or unrestricted: its availability as well as its future warranty compromise the total amount of water entering the system from each source. Therefore, the hereby shown results give us an idea of how far flows optimization could go if there were no sources restrictions. In Figure 8, sources flow evolution is shown. As it can be seen, Llobregat's mean flow is about 5 m^3/s (which is the maximum possible contribution of this source), while the lack of water necessary to satisfy the total demand is taken from Ter and Abrera. Underground sources' water cost is penalised to avoid its over-exploitation.

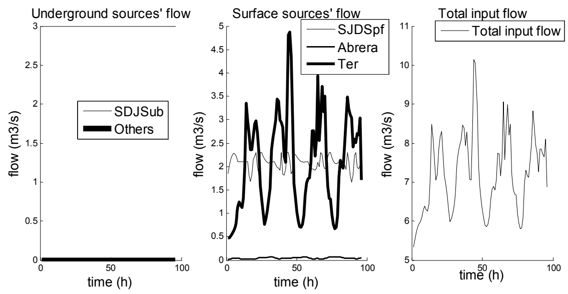

Fig. 8. Sources flow evolution for scenario 2: flow optimization.

Electrical and water cost obtained in this scenario is compared with both the current control case and the MPC case of scenario 1 (scheduled flow). In Table 3 this comparison is shown.

The first point to emphasize is the high water improvement, between 30 and 50%. As it has been seen it seems that maximizing water taken from Llobregat, water cost is clearly decreased. On the other hand electrical cost is increased, but the decrease of the total cost in this second scenario regarding to current control case and scenario 1 is important. In the next section, in Table 4, a brief summary with results of these two scenarios presented is shown.

Table 3. Improvements between the Flow optimization scenario and Current control strategy and Scheduled flow scenario

Day	Current control (in %)			Scheduled flow (in %)		
	Electrical	Water	Total	Electrical	Water	Total
1	18,92	-50,70	-27,63	54,99	-50,70	-21,59
2	14,04	-32,56	-16,41	27,51	-32,56	-13,23
3	26,29	-43,91	-21,45	59,08	-43,91	-15,91
4	26,09	-44,43	-22,36	54,86	-44,43	-17,57

5.4.3 Comments to the results

It is important to remark that these two scenarios have been important for many different factors:

- Adjustment and test of the modelling and optimisation tool used.
- To find which the behaviour of the electrical and water costs is with reference to water sources' management, especially related to Llobregat and Ter ones.
- To evaluate the potential of the optimisation tool used to optimise the management of the network in different situations: scheduled flow (scenario 1) and flow optimization (scenario 2), by the comparison with the current control strategy.

In Table 4 a brief summary of results presented is shown, as a mean of four days of study. The costs of scenario 1 and 2 are referred to current control values.

Table 4. Summary of results for scenarios presented.

Cost	Current control	Scheduled flow	Flow optimisation
Electrical	32,77%	-18,26%	+21,34%
Water	67,23%	0	-42,90
Total	100%	-5,94%	-21,96%

From this table conclusions that can be emphasized are:

- Maximizing Llobregat's source flow to optimize total cost.
- Flow optimization allows higher improvement with regard to fixed real flows. But remember that it is a theoretical solution, as it has been described in section 5.4.2.
- Ter total cost (only water cost because there is no pump) is higher than the Llobregat one (water and electrical cost associated). This fact, sources behaviour and results of both test scenarios indicate that the electrical and water costs are directly proportional to Llobregat's and Ter's flow respectively, while total cost is minimised by maximising Llobregat's source contribution.

6. CONCLUSIONS

Predictive control techniques provide useful tools for generating water management strategies in large and complex water supply and distribution systems, which may be used for decision support, as well as for fully automated control of a water network. This work describes the use of predictive control techniques for flow management in a large water system, involving supplies, production plants and water transport into the distribution areas. The paper presents the application of a unified approach to the water system management including supplies, production, transport and distribution areas. The modelling and predictive control solutions are designed for real-time decision support. The hydraulic modelling relies on simple, but representative, dynamic equations and recursive real-time parameter calibration using updated data from telemetry. Demand predictions are also dynamically updated. The potential of these techniques for real-time control of water supply and distribution has been shown with two representative examples of complex operational situations. The test scenarios are based on real situations which are known to have caused difficulties to operators and, in some cases, severe effects on the service to consumers. The application described in the paper deals with these scenarios successfully, by producing control strategies that rearrange flows, production plant levels, pumping from underground sources, etc. in a way that demands are met at all times with overall management goals respected. This type of decision support is extremely useful for water system operators in large-scale systems, especially those involving several different water management levels (supply, production, transport, distribution), where the control solutions may not obvious be successfully implemented. Another important contribution of this work is the knowledge generalization for a large class of water systems, materialized in a user-friendly software tool which allows the user to model water networks through a graphical interface and to set predictive control goals, priorities and operational constraint specifications. The program generates hydraulic and optimization model, which are solved timely (in 5-10 minutes using a standard computer) for a real-time implementation as a decision support tool. The application developed in this project is useful for a large class of water systems.

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