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 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, safety storage volumes in the network and smoothness of the flow control actions. 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, Drinking water networks, Large-scale systems, Optimization, Demand forecast

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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. Operational control of DWNs using optimal control techniques has been largely investigated (see (Brdys and Ulanicki, 1994)). This paper proposes the use of MPC technique 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, safety water storage and smoothness in flow control actions. 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 characteristics (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 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), developed in the framework of SOSTAQUA, a broad-scope R+D+I programme led by AGBAR, funded by the Spanish Ministry of Science and Innovation. This paper is an extended version of the paper (Pascual, 2011) where preliminary results of SOSTAQUA project have been presented.

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 providing the set-points for the local controllers, which are typically based on PID algorithms. 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 tanks (to preserve the satisfaction of future demands) and smooth 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 satisfaction 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.

At the supply water basin level, strategic planning deals with sustainable use of the water resources, seasonal variations in reservoirs and water levels, etc., so that planning horizon, sampling times and control time steps 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. Model predictive control (MPC) (Camacho and Bordons, 2004; Maciejowski, 2002) provides suitable techniques to implement the operational control of water systems to improve their performance, since it allows to compute optimal control strategies *ahead of time* for all the flow and pressure control elements. Moreover, MPC allows taking into account physical and operational constraints, the multivariable input and output nature, the 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 waste-water networks 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.

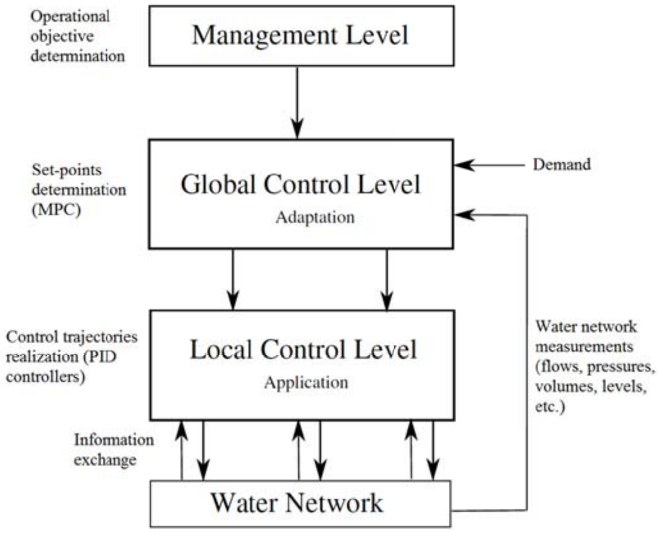


Fig. 1. Hierarchical control structure used in for the operational control of water networks

3. NETWORK AND DEMAND MODELLING FOR OPERATIONAL OPTIMAL PREDICTIVE 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 reasoning, the next subsection shows a summary of the modelling methodology used.

3.1.1 Network model and variables

A water transport and distribution system generally contains a number of flow- or pressure-control elements, located at the inlets to the network; usually water production/treatment plants. Similarly it contains flow and pressure control elements within the network, such as valves and booster pumps. These elements are controlled through a 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 $u \in \mathbb{R}^{n_u}$. 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 a telemetry system is a vector of state variables $x \in \mathbb{R}^{n_x}$. Water demand at consumer nodes may be considered a stochastic disturbance in the model. Then, $d \in \mathbb{R}^{n_d}$ 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

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

where $q_{\mathrm{in},i}(k)$ and $q_{\mathrm{out},i}(k)$ correspond to the net inflow and outflow to the i-th tank, 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

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

where $q_{\text{in},i}(k)$ and $q_{\text{out},i}(k)$ correspond to the net inflow and outflow to the i-th node, 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[1])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. States (volumes) are usually estimated from level measurements obtained from limnimeters installed inside the tanks. 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

$$E\tilde{u}(k) = 0 \tag{7}$$

where matrix E contains in rows the flows that participate in the mass balance in each node.

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

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

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

[1]Since flows entering and going out each tank are controlled by means of a valve or a pump (i.e., they do not flow by gravity), matrix A is the identity matrix. Matrix B contains only "0" and "1s" (positive or negative) reflecting if there is an actuator (pump or valve) that introduces/extracts water to the tank.

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 and it is based on the one presented in (Quevedo, 2010):

- 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 series 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.

3.2.1 Aggregated daily flow model

The aggregated 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 aggregated 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($p_{1,2}= \cos(2\pi/7) \pm j\sin(2\pi/7)$).
- *An integrator* takes into account possible trends and the non-zero mean value of the flow data.
- *An autoregressive component* to consider the influence of previous flow values within a week. For the general case, the influence of seven previous days is considered (9). However, after parameter estimation and significance analysis, the models are usually reduced implementing a smaller number of parameters

$$y(k) = -a_1 y(k-1) - a_2 y(k-2) - a_3 y(k-3) - a_4 y(k-4) \qquad (9)$$

Combining the previous components in the following way:

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

The structure of aggregate daily flow model for each demand location is therefore:

$$y_p(k) = -b_1 y(k-1) - b_2 y(k-2) - b_3 y(k-3) - b_4 y(k-4) - b_5 y(k-5) - b_6 y(k-6) - b_7 y(k-7) \tag{10}$$

The parameters $b_1, \cdots, b_7$ should be adjusted using least-squares-based parameter estimation methods and historical demand data using, f.e., the MATLAB system identification toolbox (*arx* method).

3.2.2 Hourly 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/monthly variation in the following way:

$$y_{ph}(k+i) = \frac{y_{pat}(k,i)}{\sum_{j=1}^{24} y_{pat}(k,j)} y_p(k) \quad i = 1, \cdots, 24 \tag{11}$$

where $y_p(k)$ is the predicted flow for the current day k using (10) 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, 2010).

4. MPC CONTROL OF DRININKG WATER TRANSPORT SYSTEMS

4.1 Operational goals

The immediate control goal of a drinking water network 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 production (treatment) are due to: chemicals, legal canons and electricity costs. Delivering this drinking water through the water transport network involves important electricity costs in pumping stations. Evaluating the cost of water and electricity separately allows the study of their effects on the optimal solution. For this study, this control objective can be described by the expression

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

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). The weight matrix W_e expresses the relative priority of this objective with respect to the others in the optimization process.

- *Safety storage term.* The satisfaction of water demands must 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:

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

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

- *Smoothness in flow set-points or 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 smoothness 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 the above mentioned 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:

$$\mathbb{U} = \left\{ u \in \mathbb{R}^{n_u} \middle| u^{min} \le u \le u^{max} \right\}$$
$$\mathbb{X} = \left\{ x \in \mathbb{R}^{n_x} \middle| x^{min} \le x \le x^{max} \right\}$$

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 presented in Section 3. However, only the first control input $u_{k|0}$ is actually applied to the system. The same procedure is restarted at time *k+1*, using the new measurements obtained from sensors that allow estimating the actual value of system states (volumes) that allows initializing the optimization problem (16). In this way, a feedback from the telemetry system is used, that allows the optimal control strategy to be 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
- the feasibility constraints, i.e. the limits on the state variables, such as minimum and maximum tank volumes

described in *Section 3*.

The optimization problem (16) can be efficiently solved using the tool presented in Appendix I.

Algorithm 1. MPC Algorithm

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

5. APPLICATION: THE BARCELONA WATER TRANSPORT NETWORK

As an application case study to show the performance of the proposed modelling and control approach, some results of its application off-line (in simulation) in several real scenarios in the Barcelona water network are presented. A simulator of this network has been built using MATLAB/SIMULINK and validated using real data coming from real scenarios (see Section 5.2). This allows testing the controller against a virtual reality introducing for example real demand in the simulator different from the predicted demand used by the controller. The MPC controller was implemented with the tool presented in (Cembrano, 2011) that uses GAMS/CONPOPT solver to solve the optimization problem (16) (see Appendix I).

5.1 Network description and operational objectives

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. Water is supplied from these sources to 218 demand sectors through around 4645 km of pipes.The complete transport network has been modelled using: 63 storage tanks, 3 surface sources and 7 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.

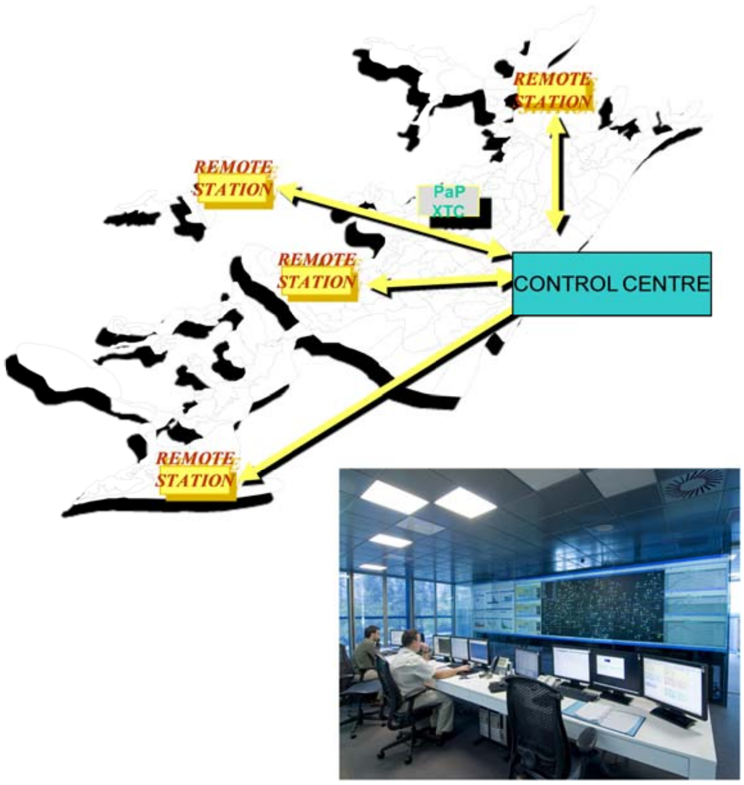


Fig. 2. Barcelona Water Network control scheme

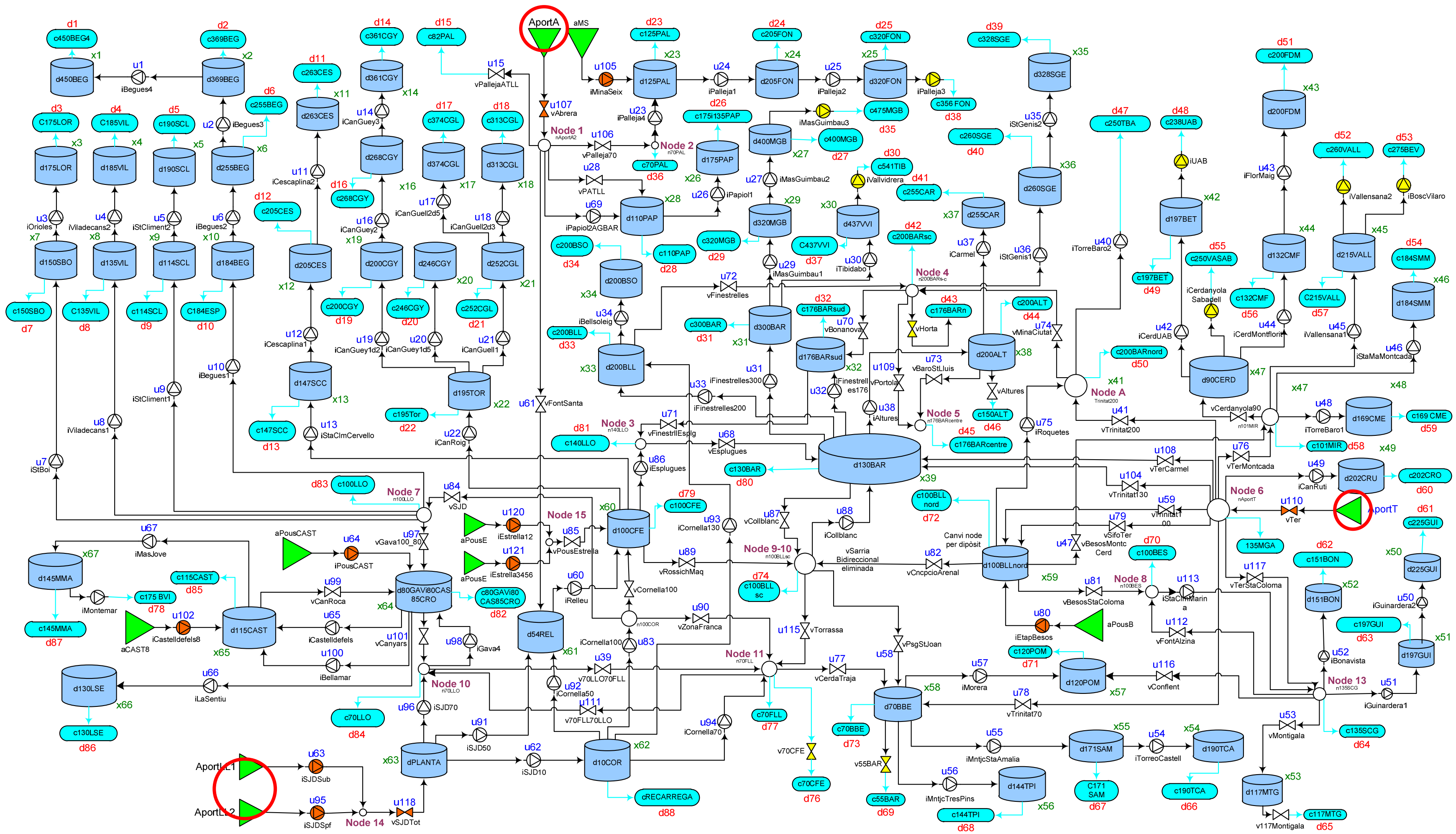
In Figure 3, the whole network representation using elements of the modelling and optimal control tool used is shown. It is a simplified model of the real system:

- Each demand is actually another more detailed network of connections to hundreds or thousands of users.

-Each actuator can integrate several pumps or valves working in parallel.

Sources are represented using a triangle. The main ones are highlighted with a circle.

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.



Last Update:
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MODEL PARAMETERS SUMMARY

63 STATE VARIABLES
129 CONTROL ACTIONS
88 DISTURBANCES
18 NODES

Fig. 3. Barcelona water network description

5.2 Simulator implementation

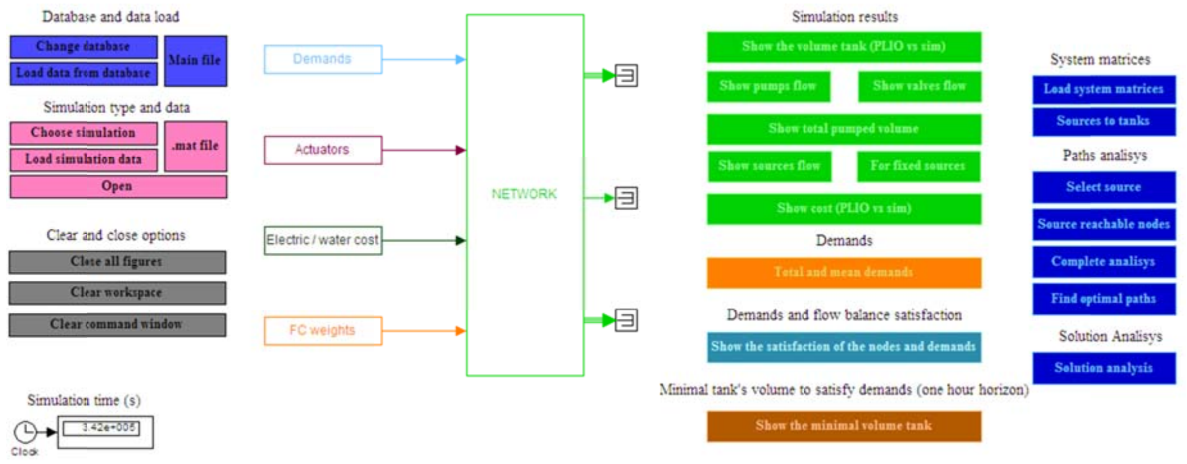
From the hydraulic model of the Barcelona water supply network, a simulator of the network has been developed using MATLAB/SIMULINK. The aims of this simulator are:

- To be used as a "*virtual reality*" to verify the implemented MPC control.

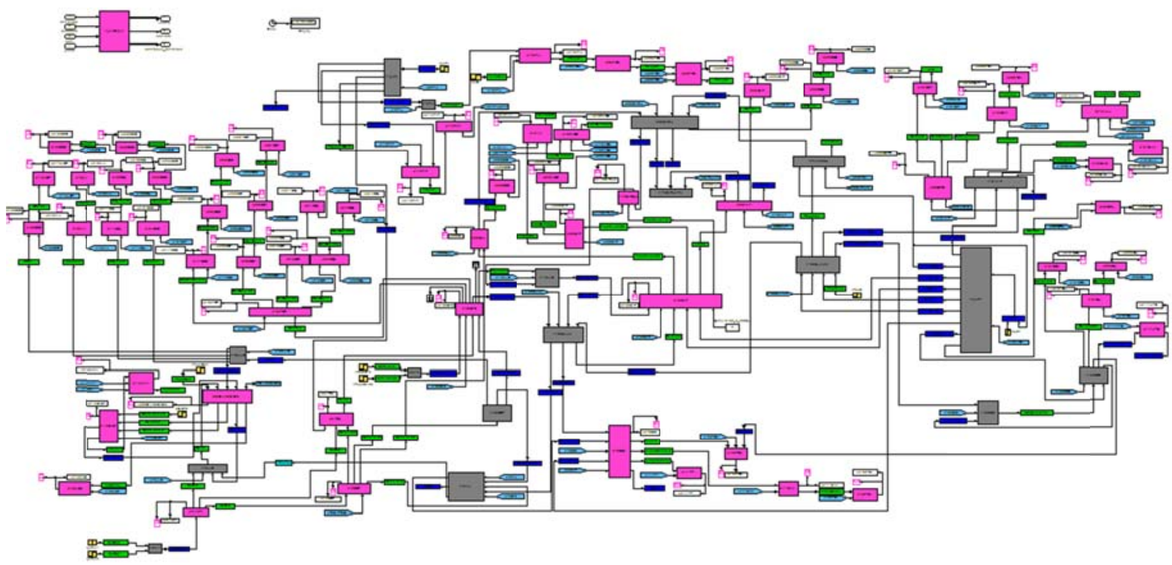
- To evaluate economical cost of any feasible control strategy; in particular those applied by operators, based on experience.

- To verify how the error in demand forecasting affect the overall performance of the MPC control system.

Figure 4(a) presents the main screen of the simulator while Figure 4(b) presents the water network model implemented using SIMULINK blocks.



(a)



(b)

Fig. 4.(a) Main SIMULINK screen of the Barcelona Network Simulator. (b) Detailed implementation using SIMULINK blocks.

The main screen of the simulator (Figure 4a) shows all the controls necessary to use it. From these controls, data from real scenarios provided by AGBAR can be loaded from a *mat* file or an Access Database by using the Matlab database toolbox. Communication between the simulator and the MPC control tool (presented in Appendix I) is done via OPC protocol as it was connected to the SCADA of the AGBAR control centre. Other controls of the simulation can be used to show graphically or numerically in the command window simulation results, input data and costs as well as the compare the performance of the MPC controller against the current experience based strategy.

5.3 Model validation

Model validation has been carried out using real data taken from AGBAR historical database to reproduce tank's volume evolution and compare them with real ones. During the model validation three points have been checked:

- Correct operational limits of tanks, pumps and valves
- Correct topology of the network
- If previous points are correct, tank's volume evolution reproduced by the simulator must be the same as real one.

So model validation process has been carried in two different stages:

- First of all, the network topology has been checked.
- Afterwards, the simulation with a real scenario has been carried out. When discrepancies are found, the operational limits and real data of the problem zone are checked and corrected when necessary.

In Figure 5, the evolution of volume at a number of tanks is shown. The simulator output is shown in blue, while red is used for the real data. (In some cases, small discrepancies between both volume curves are not associated to modelling errors but to errors in real data due to a faulty sensor).

The most important conclusion after this process is that this simulator allows making the model validation process easier. In spite of some small errors like those shown in Figure 4, the model has been validated and accepted by AGBAR as representative of the network real behaviour.

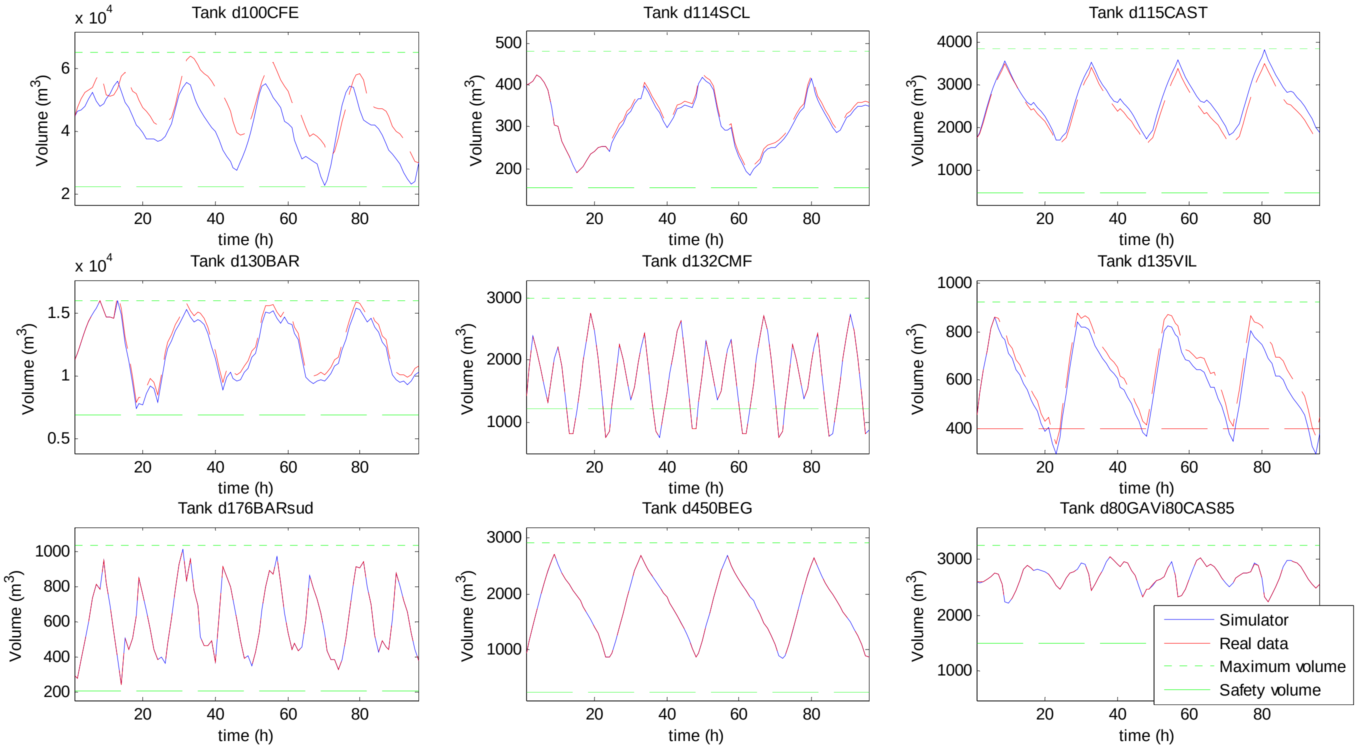


Fig. 5. Model validation based on the comparison between real volumes and the simulated ones.

The Barcelona water network is organized in different pressure levels. Figure 6 presents the different demand sectors in different colours. Each sector will be supplied through a storage tank. The distribution network that connects each storage tank with individual consumers will not be modelled in detail but will be summarised as an aggregated demand. Each demand will be modelled using a time series pattern. Figure 7 and 8 presents the validation of the daily and hourly demand forecast in the sector *c176BARsud* using the demand forecast algorithm presented in Section 3.2.

Fig. 6.Barcelona Water Network demand sectors

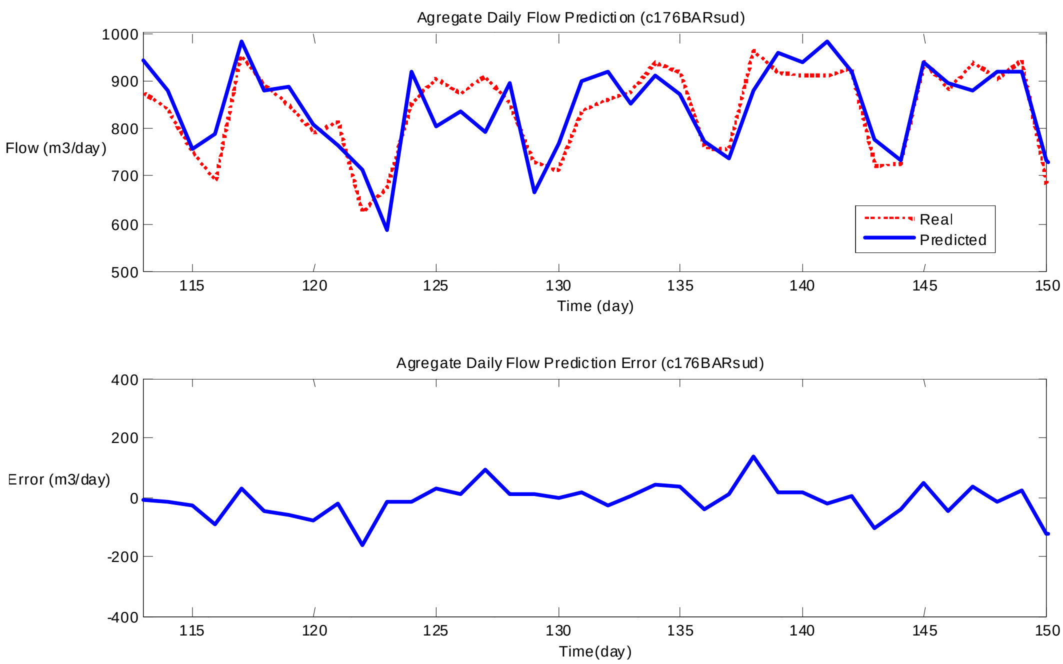


Fig. 7. Validation of the aggregate daily demand forecast corresponding to the sector *c176BARsud*

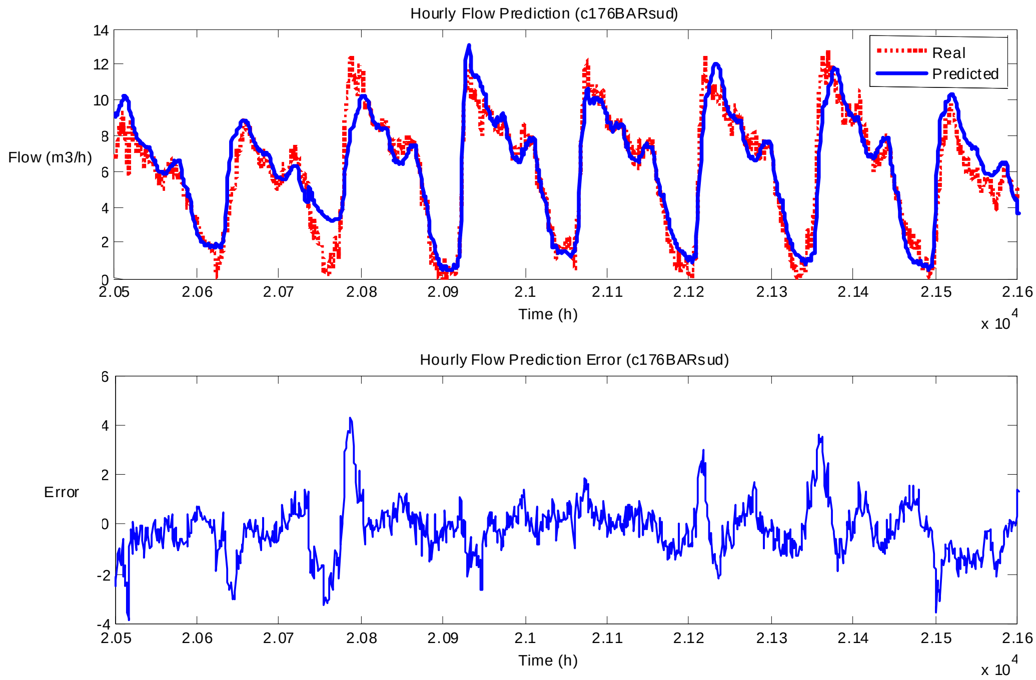


Fig. 8.Validation of the hourly demand forecast corresponding to the sector *c176BARsud*

5.4 Test scenarios

To test and adjust the MPC controller, different scenarios have been chosen. The main difference between the selected scenarios is related to source operation. So, the objective of this study is not only to show the potential of the tool used for the study, but also:

- To compare the effects of the MPC strategies with those of the currently applied control strategies.
- To show the effects of source management in the total operation cost, including electrical and water costs.

With reference to source management, two different scenarios are shown:

- Scheduled flow. In this case the flow of all sources is fixed to real values obtained from real historical data.
- Flow optimization: The optimizer calculates the flow to be abducted from each source at each time step, taking into account its operational limits, according to long term planning.

The parameters taken into account for the calibration of the model are the initial volumes and safety storage volumes in tanks, as well as the objective function weights for each of the operational goals (the economical, safety and tsmoothness factors). Objective function weights are calibrated by experimentally analysing their effects on the compromise between the operational goals, with historic data. In (Toro et al., 2011), the authors have explored multi-objective optimisation techniques to tune them in a more sophisticated way. Tank initial and safety storage volumes are taken from real historic data of each scenario, in order to make optimisation results comparable with current control strategy.

The period of both scenarios is of 96 hours (4 days), and all of them correspond to the same 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 total demanded volume for each day is obtained from the total contribution from each source. In Table 1 values of volume per day are shown.

Table 1. Total input volume for studied days

	Total input volume (m3)	Mean flow (m3/s)
23/07/2007	633694	7,334
24/07/2007	668136	7,733
25/07/2007	617744	7,150
26/07/2007	627406	7,262
Mean		7,370

In the next section, results are presented. The idea is to compare the current control with the MPC control results to quantify the improvement in terms of economic cost, which is distinguished between electrical and water cost.

5.5 Results

In all the 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 this section. For these tests the same model is used, implemented using Matlab.

5.5.1 Scenario 1: Scheduled flow

In this first scenario, source flows are 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 (pumping) cost.

The evolution of source flows is shown in Figure 9. As can be seen, in this scenario Llobregat’s mean flow is about 3 m^3/s and Ter mean flow is near to 4 m^3/s. In addition more sources are used, on average: Abrera’s source with a flow of 0.5 m^3/s and underground sources with an aggregated flow of about 0.25 m^3/s.

In Table 2, electrical and water cost in % of the total cost for the current control strategy are shown. In Table 3, costs for the MPC control as an increase or decrease % with regard to current control are presented.

Table 2. Current control strategy costs in %

	Electrical cost	Water cost	Total cost
23/07/2007	33,13	66,87	100,00
24/07/2007	34,66	65,34	100,00
25/07/2007	32,00	68,00	100,00
26/07/2007	31,29	68,71	100,00

Table 3. MPC control improvement in % for scenario 1 (scheduled flow) regarding to table 2 values.

	Electrical cost	Water cost	Total cost
23/07/2007	-23,27	+0,00	-7,71
24/07/2007	-10,56	+0,00	-3,66
25/07/2007	-20,61	+0,00	-6,59
26/07/2007	-18,58	+0,00	-5,81

Water production cost (acquisition and treatment) 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 10some tank volume evolution can be seen, as well as maximum and security volumes.

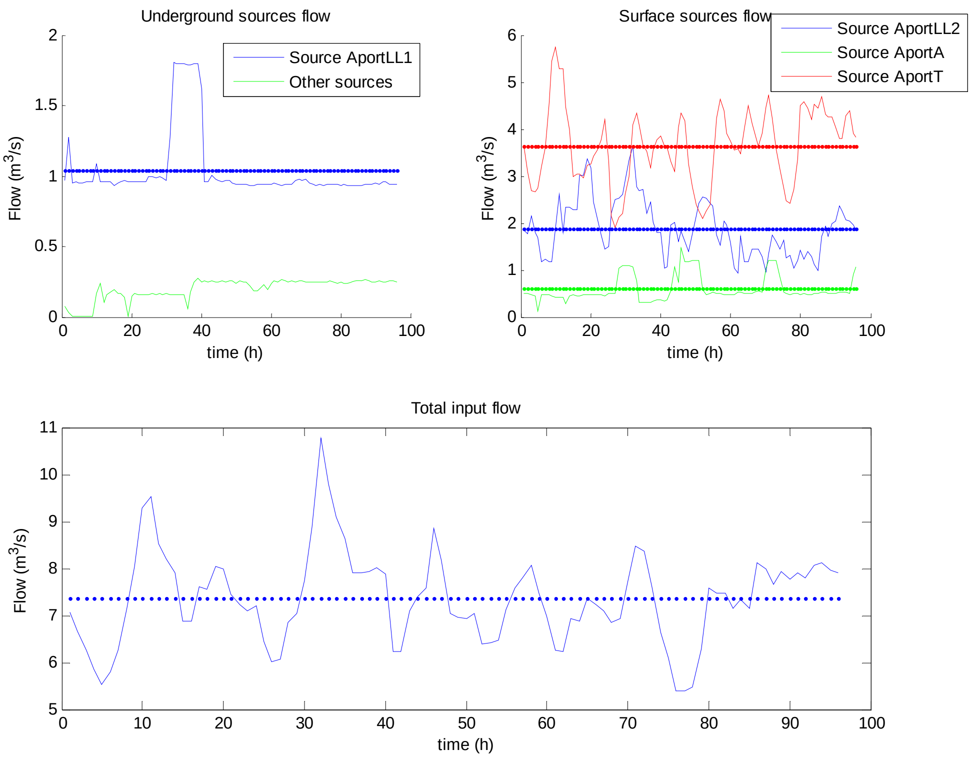


Fig. 9. Sources flow evolution for scenario 1: scheduled flow.

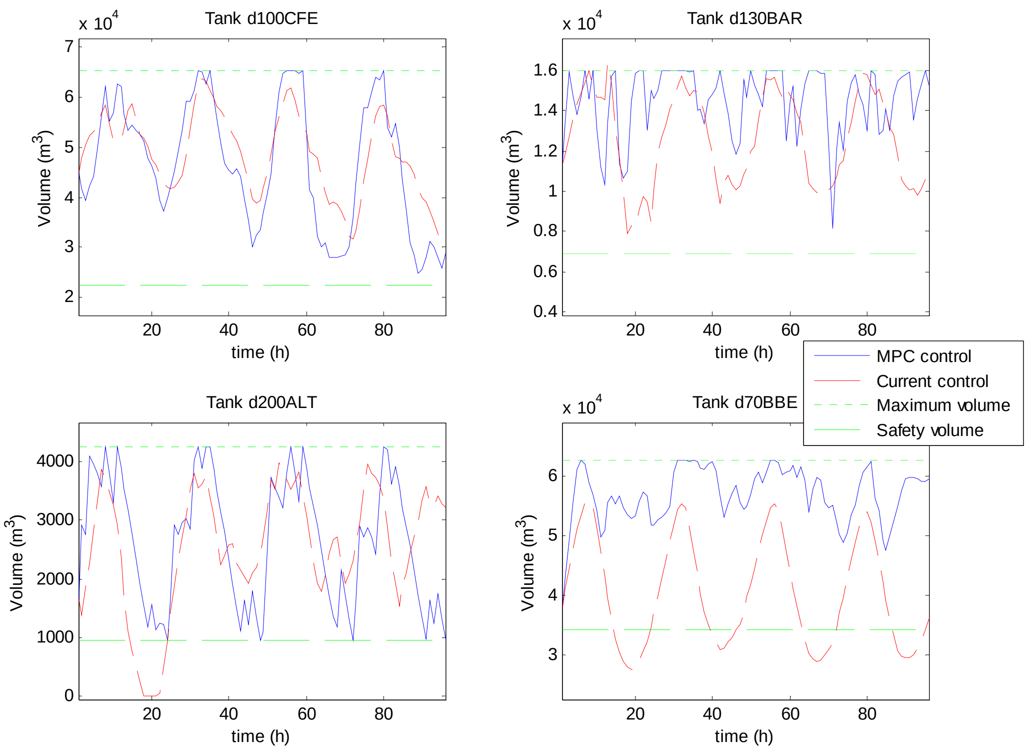


Fig. 10. Some tanks volume evolution: current control and MPC control comparison.

Below, in Figure 11, the effects of the smoothness term in the objective function are shown. As can be seen in pumps 1 and 2, signals obtained with the smoothness term in the objectives function are clearly smoother, while in the third one no differences are appreciated.

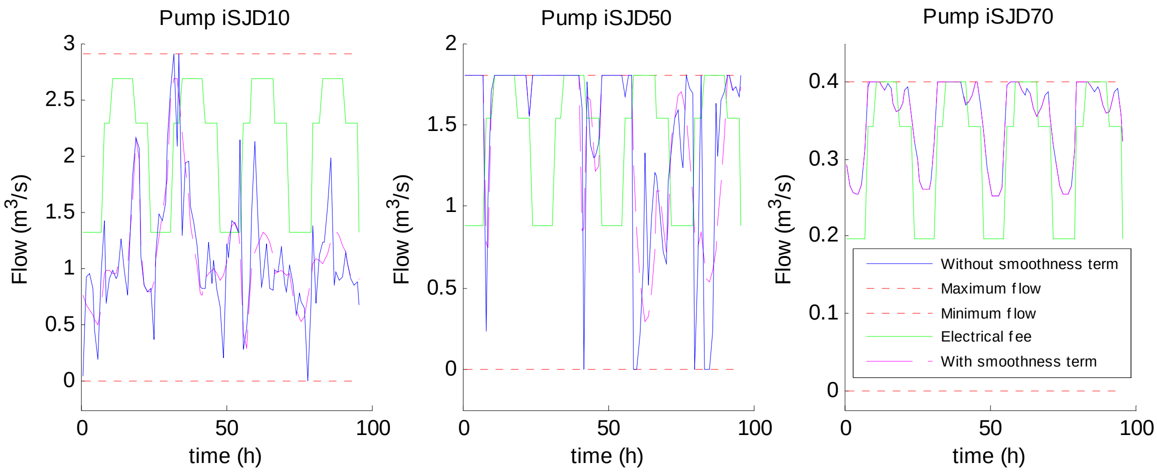


Fig. 11.Smoothness term effects on pumping operation

The smoothness 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 12, 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. 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.

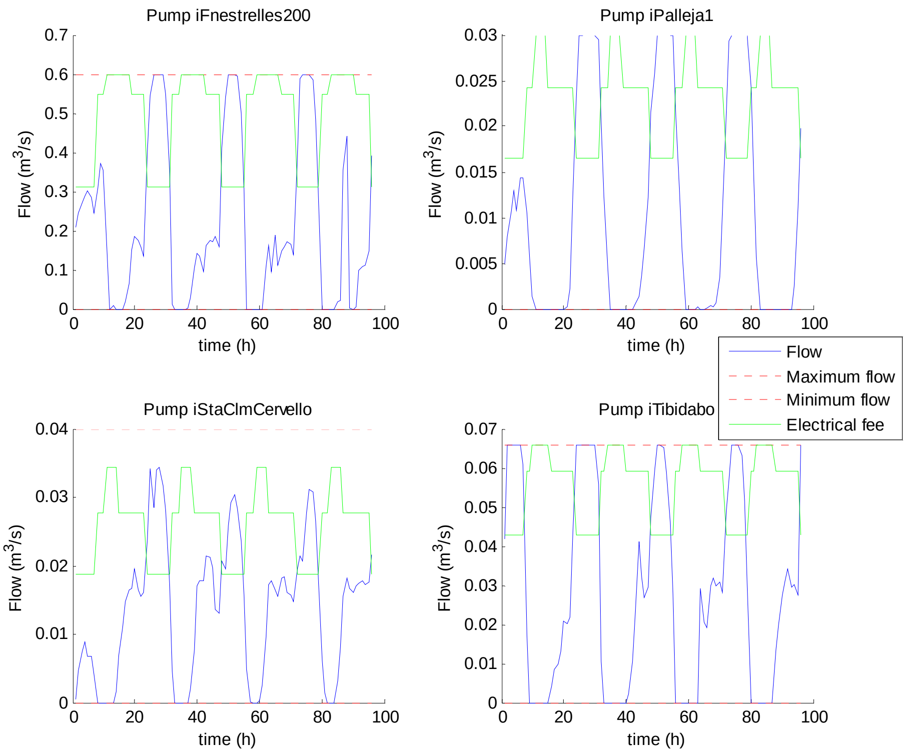


Fig. 12. Electrical fee effects on pumps operation

5.5.2 Scenario 2: Flow optimization

In this second scenario, the source flows are 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 13, 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.

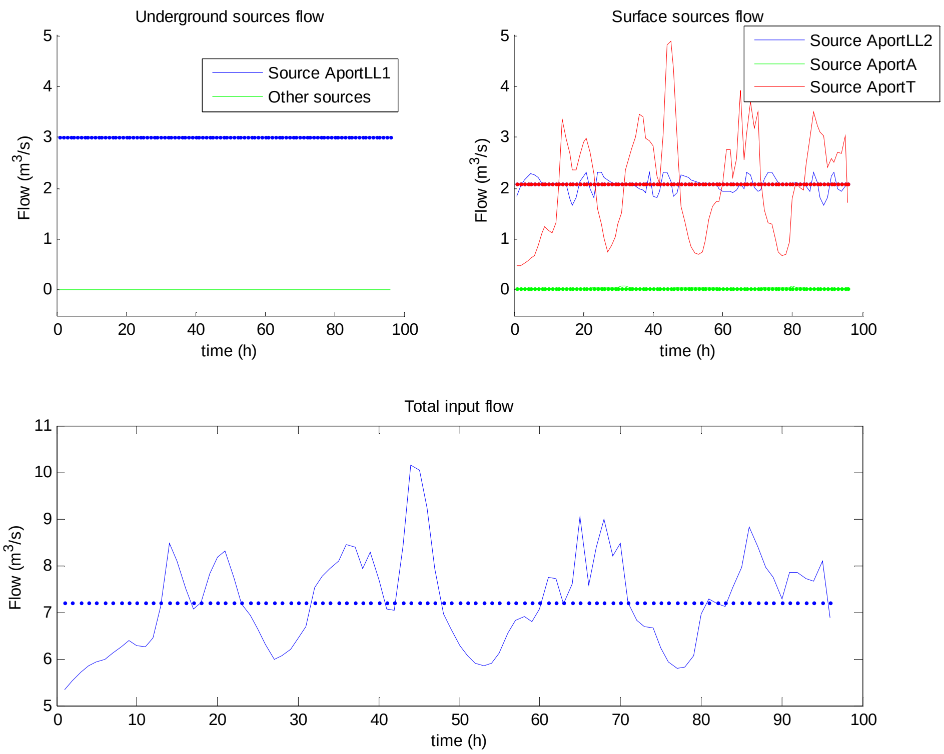


Fig. 13. Sources flow evolution for scenario 2: flow optimization.

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 tables 4 and 5 this comparison is shown.

The first point to emphasize is the high water improvement, between 30 and 50%. As shown, 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 6, a brief summary with results of these two scenarios presented is shown.

Table 4.Scenario 2 improvement with regard to current control case (Table 2).

	Electrical cost	Water cost	Total cost
23/07/2007	18,92	-50,70	-27,63
24/07/2007	14,04	-32,56	-16,41
25/07/2007	26,29	-43,91	-21,45
26/07/2007	26,09	-44,43	-22,36

Table 5. Scenario 2 improvement with regard to scenario 1 case (scheduled flow).

	Electrical cost	Water cost	Total cost
23/07/2007	54,99	-50,70	-21,59
24/07/2007	27,51	-32,56	-13,23
25/07/2007	59,08	-43,91	-15,91
26/07/2007	54,86	-44,43	-17,57

5.5.3 Scenario 3: Fixing main source

The two main sources of the Barcelona water network are the Llobregat and Ter rivers. Barcelona's average demand is about 7.5 m^3/s. For ecological reasons, AGBAR company uses Llobregat source at its maximum capacity which value depends on the river flow. The rest of flow is supplied by Ter source. From Figure 14, it can be noticed that both sources affect the economic cost in an inverse way. Increasing the amount of water extracted from Llobregat source reduces the water cost while increasing the electrical cost. On the other hand, the Ter source behaves on the opposite sense: increasing the amount of water extracted from this reiver reduces the electrical cost while augmenting the water cost. The reason for this behaviour is due to a smaller water price in the case of Llobregat. But, since Llobregat source is located close to the sea-level, while Ter source is in the upper part of the city, electrical costs will be higher in case of the Llobregat source since more pumping will be required to supply water from this source. In the case when sources are not fixed, the optimal combination leads to take most of the water from Llobregat source and the remaining from the Ter source.

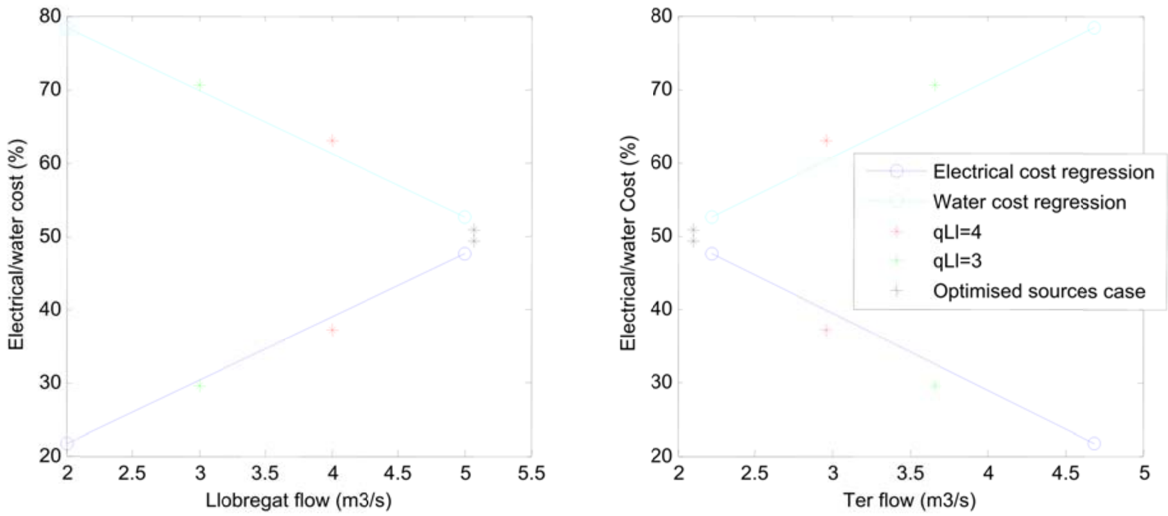


Fig. 14.Electrical and water cost when fixing Llobregat source

5.4.4 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 Terones.

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

Table 6. Summary of results for scenarios presented.

Cost	Current control	Scenario 1 (real flows)	Scenario 2 (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 because the optimiser can maximise Llobregat’s flow contribution if it is possible. Sometimes it is not possible because of reasons not related to network characteristics (operational limits of actuators and tanks).
- 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:
    - Reduction of electrical cost involves reduction of Llobregat’s contribution
    - Reduction of water cost involves reduction of Ter’s contribution.
    - Total cost is minimised by maximising Llobregat 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 improved results with respect to management goals. 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 are 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 (Cembrano, 2011) 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 is useful for a large class of water systems.

ACKNOWLEDGEMENTS

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APPENDIX I: PLIO tool

PLIO is a graphical real-time decision support tool for integral operative planning of water systems covering supply, production, transport and distribution networks. .

PLIO has been developed using standard GUI (graphical user interface) techniques and object oriented programming using Visual Basic.NET (Microsoft, 2002). PLIO uses a commercial solver, GAMS (GAMS, 2004), to determine the optimal solutions of the optimization problem associated to the predictive optimal control using nonlinear programming techniques. The tool has four modes of operation: edition, simulation, monitoring and reproducing modes (Fig. 15).

*Edition mode.*This mode allows graphically building and parameterizing the network using the palette of building blocks, defining the control objectives and generating the optimization model equations (Fig. 16). PLIO has different element libraries which allow the user to easily model the network. Elements include tanks, water demands, sensors and actuators (pumps and valves). The user may place these elements in the model using drag and drop and then connect them using pipes, aqueducts, etc. Each element in PLIO has a number of properties, which are grouped in trees. These identify the element, parameterize its characteristics, provide goals to the optimizer, define SCADA data links and database presence, etc. Once the network has been built, PLIO tests it for consistency and creates the set of optimization equations using the goals and constraints defined in each element.

*Simulation (or off-line) mode.*This mode allows network optimization off-line using the model of the controller as the simulation model and the demands from the PLIO database corresponding to a recorded real scenario as inputs. PLIO generates the optimal controls which are applied to the same network model (as a substitute of the real network). Graphical evolution of the main network variables and controls can be represented and registered in PLIO database for further study.

*Monitoring (or on-line) mode.*Network optimization in real time is carried out in monitoring mode, using the demands and measurements from network real state coming from the telemetry system, provided by the SCADA system. PLIO generates the optimal controls, which are applied to the real network only after confirmation by an operator. Graphical evolution of the main network variables and controls can be represented and registered in PLIO database for further study.

Reproduction mode. This mode allows the reproduction of network state evolution under specified operation conditions and control set-points (optimal or other). PLIO provides a graphical representation of the main variable evolution in a real or simulated scenario.

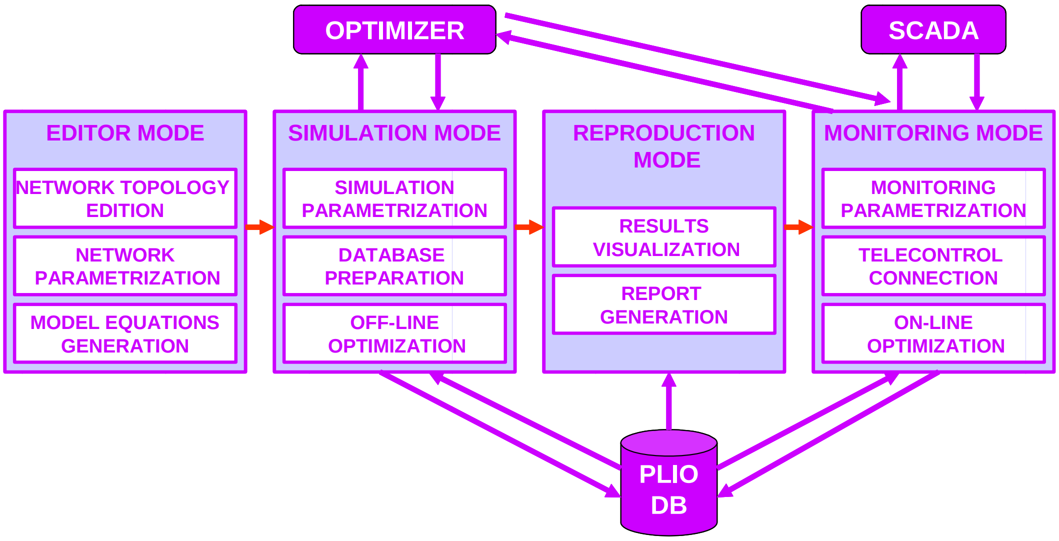

Fig. 15. PLIO operation modes

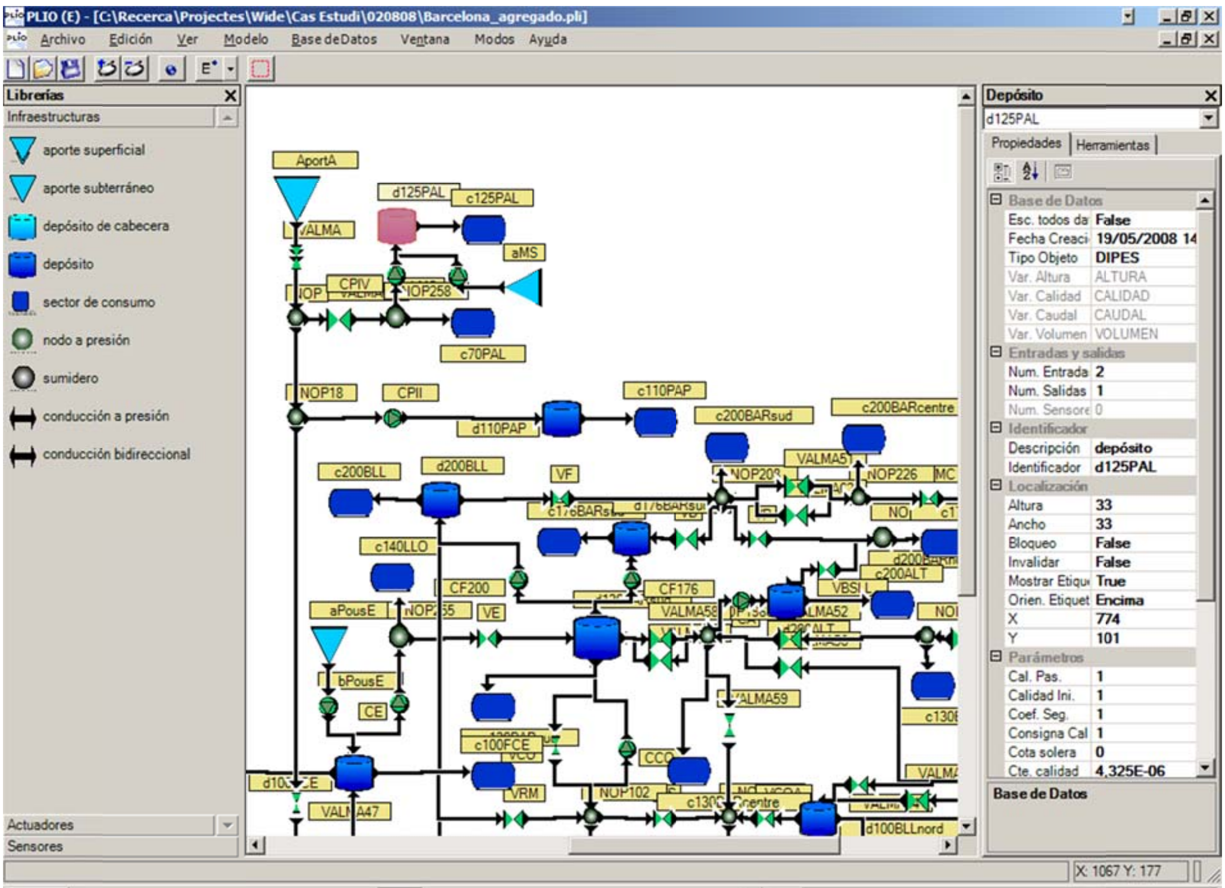

Fig. 16. PLIO in edition mode

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