PLIO: A Generic Tool for Real-Time Operational Predictive Optimal Control of Water Networks

G. Cembrano[♦], J. Quevedo[♦], V. Puig[♦] R. Pérez[♦], J. Figueras[♦],

J. M. Verdejo[#], I. Escaler[#], G. Ramón[#], G. Barnet[#], P. Rodríguez[#], M. Casas[#]

[♦]*Automatic Control Department and Industrial Robotics Institute*

Technical University of Catalonia (UPC) and CSIC, Rambla Sant Nebridi, 10, 08222 Terrassa,

Spain

phone : +34 9373986327 fax : +34 9373986328

e-mail: vicenc.puig@upc.edu

[#] *Clavegueram de Barcelona S.A., Acer, 16 - 08038 Barcelona, Spain*

Abstract: This paper presents a generic tool, named PLIO, that allows to implement the real-time operational control of water networks. Control strategies are generated using predictive optimal control techniques. This tool allows the flow management in a large water supply and distribution system including reservoirs, open-flow channels for water transport, water treatment plants, pressurized water pipe networks, tanks, flow/pressure control elements and a telemetry/telecontrol system. Predictive optimal control is used to generate flow control strategies from the sources to the consumer areas to meet future demands with appropriate pressure levels, optimizing operational goals such as network safety volumes and flow control stability. PLIO allows to build the network model graphically and then to automatically generate the model equations used by the predictive optimal controller. Additionally, PLIO can work off-line (in simulation) and on-line (in real-time mode). The case study of Santiago-Chile is presented to exemplify the control results obtained using PLIO off-line (in simulation).

Keywords: Real-time control, Water systems, Predictive control, Optimal control, Decision support.

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 and quality levels make water management a challenging problem.

Many modern water systems are operated through centralized or distributed telemetry and telecontrol systems. In most cases, network operation is carried out using empirical rules and 'historic' strategies, which were result of years of operational experience and empirical results. While these may generally be adequate, the best operational policies may be very complex to determine in large-scale interconnected systems. Thus, decision support systems for operational control, which are based on mathematical models of network operation and optimal control techniques, provide useful guidance for efficient management of water networks. Analysing the literature, optimal control based techniques have been shown to be very useful for strategy computation in drinking water management, at different levels, namely, as for the integrated water resources/watershed planning and management with medium or long-term horizons (e.g. Westphal, *et al.* 2003; Nitivattananon *et al.* 1996; Tu *et al.* 2005) and for water distribution network 24-hour operation and pump scheduling. (e.g. Brdys and Ulanicki 1994; Maksimovic *et al.* 2003; Cembrano et al. 1999; 2000; Butler and Memon, 2006; Jamielson *et al.* 2007, Shamir and Salomons, 2008).

A review of existing software tools related to operational planning and control of water systems shows a few interesting contributions, such as:

- SAPHIR, a decision-making support tool developed by CIRSEE and DERCETO AQUADAPT (Bunn and Wooley, 2001). This is a real-time pump scheduling software for a 24-hour horizon developed by Derceto Ltd (UK) and intended for energy minimization in pressurized pipe networks, based on dynamic programming and linear modelling.

- SCA-Red, a software developed by the REDHISP group (Hydraulic Network and Pressure System Group), Polytechnic University of Valencia (Spain) (Bou *et al.*, 2006), for pressurized networks, based on the use of EPANET hydraulic models and a the software, ENCOMS (Rao, 2005). This last is an optimization system for energy cost minimization, based on adaptive genetic algorithms and neural networks, with a 24 to 48-hour horizon.

- Other related tools, such as WEAP (USA) (Yates *et al.*, 2005), WATHNET (Australia) (Kuzcera, 1997), AQUATOOL (Spain) (Andreu *et al.*, 1996) and AQUARIUS (USA) (Díaz et al., 2000), are concerned with the problem of long-term planning of water resources in open channels at a watershed scale, and therefore do not address the operational 24-hour optimal control.

The main contribution of this paper is to present a ***general-purpose decision support tool***, named PLIO, that allows to apply and implement in real-time predictive optimal control techniques in large-scale water systems. An important feature of this tool as compared to the existing tools mentioned above is the application of a unified approach to the complete drinking water system including supplies, production, transport and distribution and, therefore pressurized and open-channel dynamics, simultaneously. The modelling and predictive control problem solution algorithm in PLIO are designed for real-time decision support, in connection with a supervisory control and data acquisition system. The hydraulic modelling relies on simple, but representative enough, dynamic equations whose parameters are recalibated on-line using recursive parameter estimation and real data obtained from sensors in the network. Demand forecast models, based on time series analysis, are also dynamically updated. The real-time calibration using recursive parameter estimation methods contributes to dealing with hydraulic uncertainty. This modelling choice, as well as the optimization method selection allows PLIO to deal with very large scale systems. Another distinguishing feature in PLIO is its capability to accommodate complex operational goals. PLIO tool has been developed in a project carried out cooperatively by the AGBAR Group (Aguas de Barcelona) at CLABSA, Barcelona, and SAC (the Advanced Control Systems Group) at UPC (Universitat Politècnica de Catalunya), for Aguas Andinas, the water supply and distribution company in Santiago-Chile.

The structure of the paper is the following: In *Section 2,* the operational control of water networks is reviewed and PLIO tool is introduced*. Section 3* presents the control oriented modelling approach used in PLIO 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 embedded in PLIO. *Section 5* illustrates how this tool works through the application to the Santiago-Chile water network using several selected real scenarios using PLIO off-line (in simulation). Conclusions and on-going work are outlined in *Section 6.*

2. PLIO: A TOOL FOR OPERATIONAL CONTROL OF WATER NETWORKS

2.1 Operational control of water network using model predictive control

In most water networks, the operational control is managed by the operators from the telecontrol centre using a SCADA 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 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.

Model predictive control (MPC) (Camacho and Bordons, 2004; Maciejowski, 2002) provides suitable techniques to implement the operational control of water control 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 to take into account physical and operational constraints, the multivariable and large-scale 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, 2008) (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. In this global control structure, 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.

2.2 The 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. 1a).
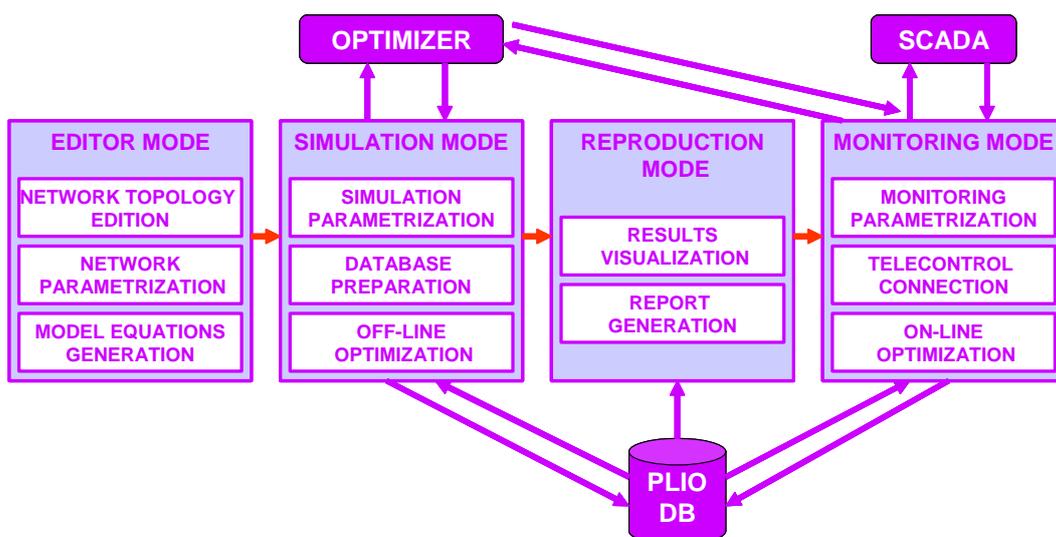
(a)
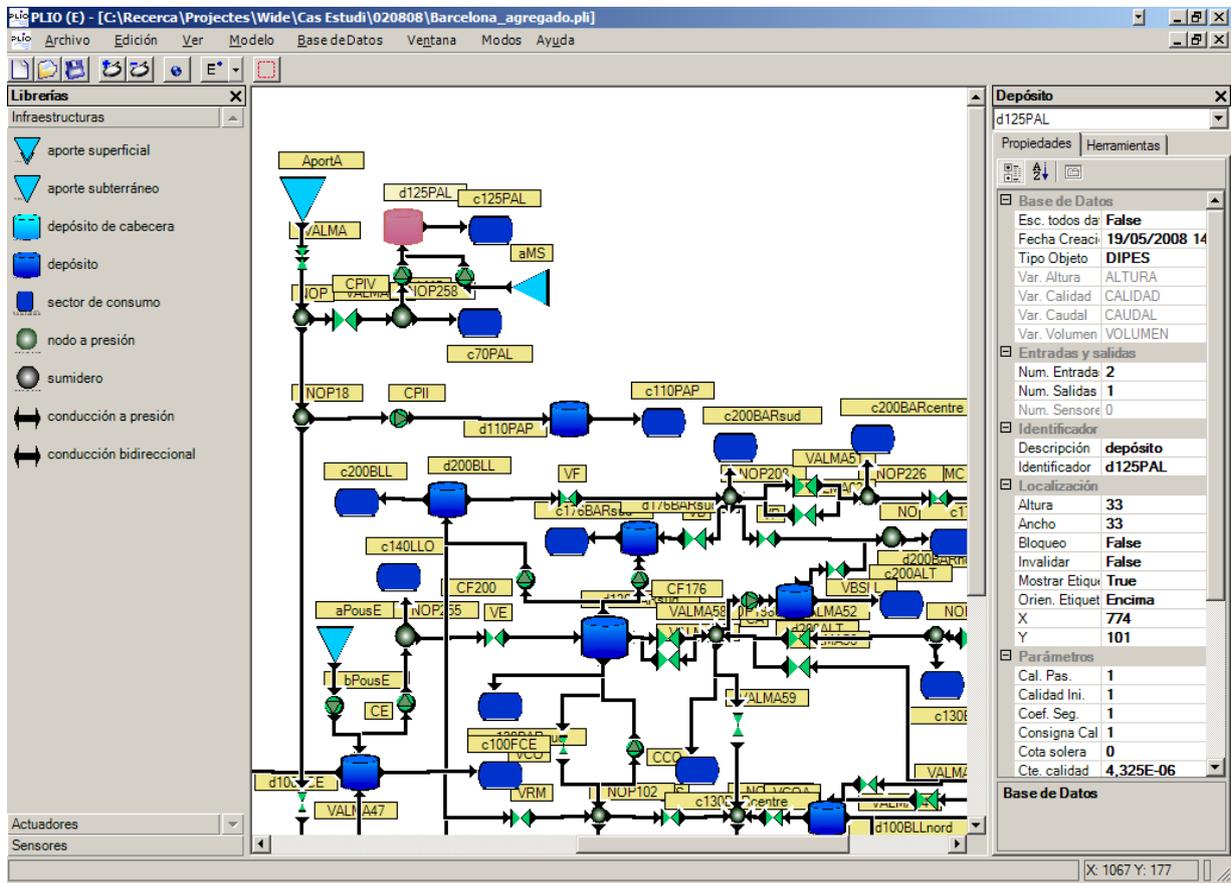
(b)

Fig. 1. (a) PLIO operation modes. (b) PLIO in edition mode

Edition mode. This mode allows to graphically build and parameterize the network using the palette of building blocks, define the control objectives and generate the optimization model equations (Fig. 1b). PLIO has different element libraries which allow the user to easily model the network. Elements include reservoirs, tanks, water demands, sensors and actuators. 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.

3. NETWORK AND DEMAND MODELLING IN PLIO

3.1 Network model in PLIO

The control oriented model of a water network allows to predict the effect of control actions on all the network elements. This model should be representative of the hydraulic dynamic response while at the same 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 following subsection shows a summary of the modelling methodology used in PLIO.

3.1.1 Network model and variables

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(k)*, 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

Flow and pressure variables in a water network have hydraulic couplings. For example:

a) *Open channels*: In these elements, upstream and downstream flow are coupled through hydraulic relationships. In particular, the effect of a flow change upstream produces an effect downstream with a

certain time-delay and dynamics. For the purpose of on-line control a simpler but efficient representation consists of expressing the relationship between downstream and upstream flow as a finite-impulse-response (FIR) input-output model with a time delay:

$$q_{out}(k) = a_0 q_{in}(k-\tau) + a_1 q_{in}(k-\tau-1) + ... + a_s q_{in}(k-\tau-s) \tag{2}$$

where: q_{in} is the upstream flow value; q_{out} is the downstream flow value; τ is the average time-delay between the upstream and downstream points, which must be estimated using historic data; s the order of the dynamic model; a_0, a_1,...,a_s are parameters of the response dynamics, which must be estimated using data from telemetry.

b) *Pressurized pipes:* Instantaneous flow in pipes is related to head-loss between the extremes and this relationship is usually modelled through well-known nonlinear approximations, such as the Hazen-Williams equations (see e.g. Jeppson, 1983, Johnson,1998)

$$q_{ij}(k) = c_{ij}(h_i(k) - h_j(k))^l \tag{3}$$

where: q_{ij} is the flow through a pipe between nodes i and j; h_i and h_j are the head values at nodes i and j respectively; c_{ij} is a parameter depending on pipe characteristics that should be calibrated using measurements from the telemetry system and historic data; l is the exponent representing the nonlinearity of this relationship.

c) *Reservoirs*: In the reservoirs, the following mass balance is established between the volume and input/output flows

$$V_i(k+1) = V_i(k) + \Delta t(q_{i,in}(k) - q_{i,out}(k)) \tag{4}$$

where: V_i is the water volume stored in the reservoir i; $q_{i,in}$ and $q_{i,out}$ are respectively the input and output flows of the reservoir i; Δt is the discretization step control sampling time.

Taking into account the geometry of the reservoir, an experimental relation between the volume and the reservoir level/head can be established what allows to estimate the volumes (states).

d) *Treatment plants*: Although sophisticated models exists for treatment plants, they are fairly complex. Thus for operational control purposes a simple black-box input/output model is usually used (Brdys and Ulanicki 1994). This can be done because the plant is separated from the rest of the distribution system by a contact tank and the treatment plant has much faster dynamics that the rest of the system. This leads to the following relation reflecting the two main phenomena (processing time and water loss):

$$q_{i,out}(k) = K_i q_{i,in}(k - \tau_i) \tag{5}$$

where: $q_{i,in}$ and $q_{i,out}$ are respectively the input and output flows of the treatment plant i; K_i is the plant gain and $(1\text{-}K_i)$ measures the water loss; τ_i is the time-delay between the input and output points associated to the treatment time, which must be estimated using measurements from the telemetry system and historic data.

e) *Network structure*: The structure in a water network imposes flow and pressure relationships between different elements, e.g. mass conservation in nodes

$$\sum_i q_{in,i}(k) = \sum_j q_{in,j}(k) \tag{6}$$

where $q_{in,i}(k)$ and $q_{out,j}(k)$ correspond to the i-th node inflows and the j-th node outflows, respectively, given in m^3/s .

f) *Control elements*: Control elements such as valves or pumps impose relationships between the flows and pressures of their upstream and downstream conduits. PLIO provides the flow set-points for the control elements assuming that a local controller is already operating in the field.

3.2 Model for predicting the water demand

The demand forecasting algorithm used in PLIO consists of two levels. At the upper level, a time-series modelling to represent the daily aggregate flow values. At the lower level, a set of different daily flow demand patterns according to the day type to cater for different consumption during the weekends and holidays periods. Every pattern consists of 24 hourly values for each daily pattern. 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 (Quevedo, 2010).

3.3 Model calibration

Some of the functional elements in PLIO require a specific parameter calibration; namely: open channels (see Eq. (2)), pressurized pipes (see Eq. (3)) and treatment plants (see Eq. (5)). This is carried out in two steps. Initially, an off-line calibration is performed with field data and historic records. Additionally, in order to reduce the modelling uncertainty, an on-line calibration procedure, based on the recursive least-squares estimation algorithm with forgetting factor (Ljung, 1999) is used to update the parameter calibration as new data become available.

4. MPC CONTROL OF WATER SYSTEMS IN PLIO

4.1 Operational goals and constraints

The operation control goals that can be considered using PLIO are following:

- *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 to appropriate pressure levels through the water transport network involves important electricity costs in pumping stations. This control objective can be described by the expression

$$J_1(k) = W_\alpha(\alpha u(k)) + W_\gamma(\gamma(k)u(k)) \tag{7}$$

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 objective is used, as follows:

$$J_2(k) = \begin{cases} 0 & if \quad x(k) \geq \beta \\ (x(k)-\beta)^T W_x(x(k)-\beta) & if \quad x(k) \leq \beta \end{cases} \tag{8}$$

where β is 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 usually requires smooth flow set-point variations, to avoid overpressures which can cause structural damage and leaks. To obtain such smoothing effect, a third term in the objective function to penalize control signal variation between consecutive time intervals, i.e., this term is expressed as

$$J_3(k) = \Delta u(k)^T W_u \Delta u(k) \tag{9}$$

- *Pressure control*: Controlling pressure is a good means to minimize leaks. To this aim, PLIO allows the user to define pressure set-points at any desired locations in the network to avoid overpressures by introducing an additional term in the objective function as follows:

$$J_4(k) = (u(k) - \gamma)^T W_p (u(k) - \gamma) \tag{10}$$

where γ is the desired pressure set-point at the considered control point and matrix W_p defines the weight of the objective in the cost function.

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

$$J = \sum_{k=0}^{H_p-1} J_1(k) + \sum_{k=1}^{H_p} J_2(k) + \sum_{k=0}^{H_p-1} J_3(k) + \sum_{k=1}^{H_p} J_4(k) \tag{11}$$

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

Additionally, operational "good-practice" bounds on these variables may exist. For example, for safety reasons, water tanks are usually operated between minimum and maximum volume values other than the physical limits. Similar operational bounds may apply in boreholes, reservoirs or river supply sources for water conservation or other policies.

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). According to this algorithm, at each time step, a control input sequence of present and future values is computed to optimize the performance function *J* , 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 of sequence 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*.

Algorithm 1. PLIO Control Algorithm

1: $k=0$
2: **loop**
3: $x(k|0) \leftarrow$ Estimate network state from measurements using an Kalman Filter (Simon, 2006).
4: $\theta(k) \leftarrow$ Estimate network parameters from measurements using the Recursive Least Squares (RLS) algorithm (Ljung, 1999) .
5: $\tilde{d}_k = \left(d(k|0), d(k|1), \cdots, d(k|H_{p-1}) \right) \leftarrow$ Estimate demands from measurements and time series demand forecast model described in (Quevedo, 2010).
6: $\tilde{u}_k = \left(u(k|0), u(k|1), \cdots, u(k|H_{p-1}) \right) \leftarrow$ Solve optimal control problem given by

$$\min_{\tilde{u}_k} \sum_{k=0}^{H_p-1} J_1(k) + \sum_{k=1}^{H_p} J_2(k) + \sum_{k=0}^{H_p-1} J_3(k) + \sum_{k=1}^{H_p} J_4(k)$$

subject to:

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

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 obtain

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

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

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

7: Apply control action $u(k|0)$
8: $k=k+1$
9: **end loop**

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5. APPLICATION: THE SANTIAGO WATER NETWORK

As application case study to show the performance of the PLIO tool results of its application off-line (in simulation) in several real scenarios are presented.

5.1 Network description

The Santiago water network supplies water to approximately 5 million consumers. The main supplies come from a number of mountain sources, such as natural or man-made reservoirs. Water from the mountain supplies is transported to 6 main treatment plants through a network of some 65 km of rivers and open channels. It takes an average of 12 hours for water to go from the sources to the plants. After treatment, water is delivered to the consumer areas by means of three parallel (open channel) aqueducts spanning a distance of approx. 20 km.

Water is drawn from the aqueducts through valves or pumps into pressurized sections to meet consumer demands. Pressurized areas contain tanks to store water at appropriate pressure levels to meet demands. Alternative water sources, such as boreholes exist in most of the consumer areas and pressure control is achieved through the use of valves or booster pumps.

The complete supply and transport network has been modelled using: 2 mountain reservoirs, 6 treatment plants, 186 open channel sections, 281 pressure mains, 99 tanks, 88 valves and 39 pumping stations (Fig. 2). The network is controlled through a SCADA system with sampling periods of 1 hour. For the predictive control scheme a prediction horizon of 24 h is chosen. Additionally, a historic record of the previous 24 h is used to account for delays in the open channel sections. This record is updated at each time interval.

The network model and its predictive optimal control have been implemented using PLIO tool described in this paper. As discussed in *Section 3.3*, the parameters of the network element model are calibrated off-line using real data and the obtained from the telemetry system and historic records. Figure 3 shows the results of the calibration of the model of the open-channel model (see Eq. (2)) corresponding to one reach of one of the main aquaducts: Acueducto Paralelo. From this figure it can be observed that the control oriented model approximates quite accurately the real flow.

The predictive optimal control of the Santiago network has been solved successfully off-line using PLIO in a number of scenarios based on real operation situations and data. PLIO has recently been implemented on line in Santiago and its testing and validation phase is currently underway. At each 1-hour interval, state-variable values are read from the SCADA, the optimization problem for 24 hours is created and solved and control-element set-points and results are stored in a database for validation, as compared to manual operation.

5.2 Test scenarios

Two scenarios were chosen to show the potential of the PLIO tool for computing optimal control strategies in complex operational situations. Each scenario contains 3-day data, gathered from real historic records of the Santiago network. The first scenario (referred to as *Scenario 0*), was built using data of one standard operation work day, with no special incidences, reproduced for three consecutive days. The second scenario (named *Scenario 1*) reproduces a sudden drop in the demand, which occurs due to an unexpected rain in summer (people drinks less because temperature decreases).

5.3 Results

Figure 4 shows the hourly demand curve at one consumer point for three days corresponding to *Scenario 0* (thick line) and *Scenario 1* (dash line). This last scenario presents a demand decrease on the second day and a return to a normal demand on the third day.

As result of this drop in the demand, Figure 5 shows how the PLIO system generates a control strategy that produces a lower water flow in one of the aqueducts (dash line) during the lower-demand period, as compared to the normal-demand flow strategy (thick line).

Moreover, there is an increase in storage volume in tanks. Figure 6 shows the volume at one important reservoir due to reduced demand (dash line) compared to the normal situation (thick line). The dash line shows the "safety volume threshold". Solutions producing much lower storage volumes are penalized in the optimization process.

Finally, the control strategy corresponding to this scenario for a valve regulating the inlet to a consumer area is shown in Figure 7 (dash line). A reduced inlet, as compared to the normal situation may be observed (see Figure 7 (thick line)) as a consequence of the demand reduction.

Fig. 2 Santiago water network description using PLIO elements
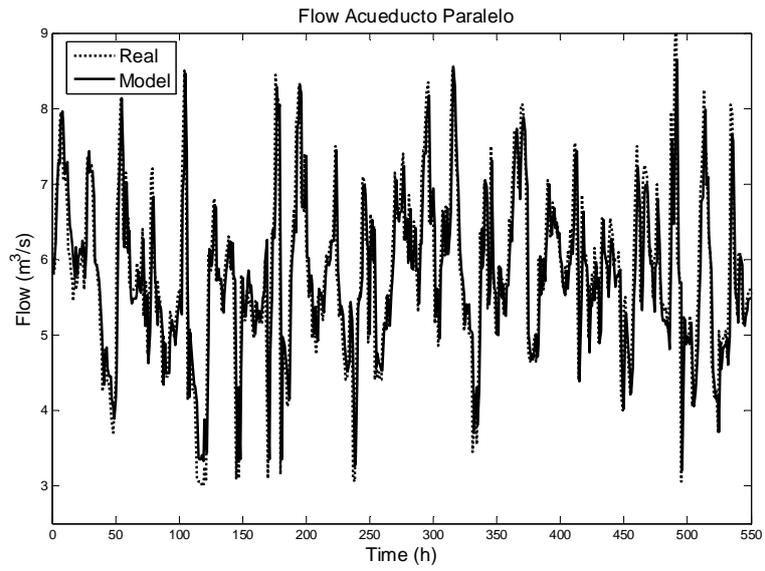
Fig. 3. Modelled vs. real downstream flow at Acueducto Paralelo
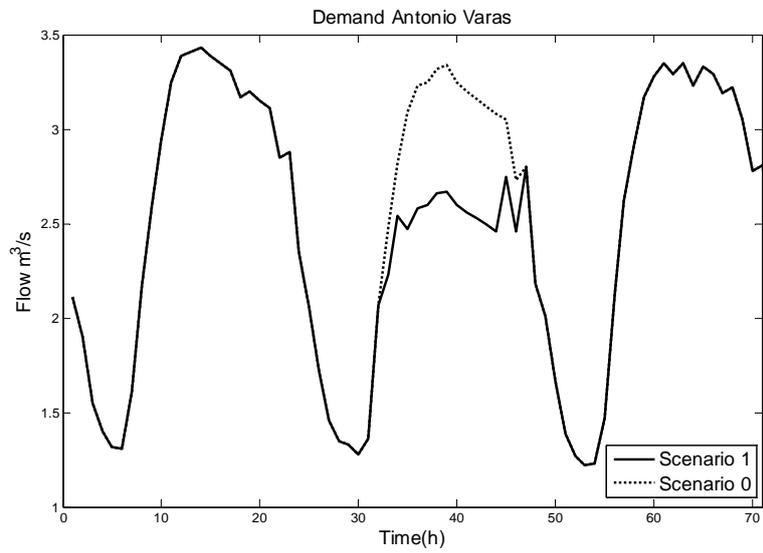
Fig. 4. Demand curve at a Antonio Varas consumer area
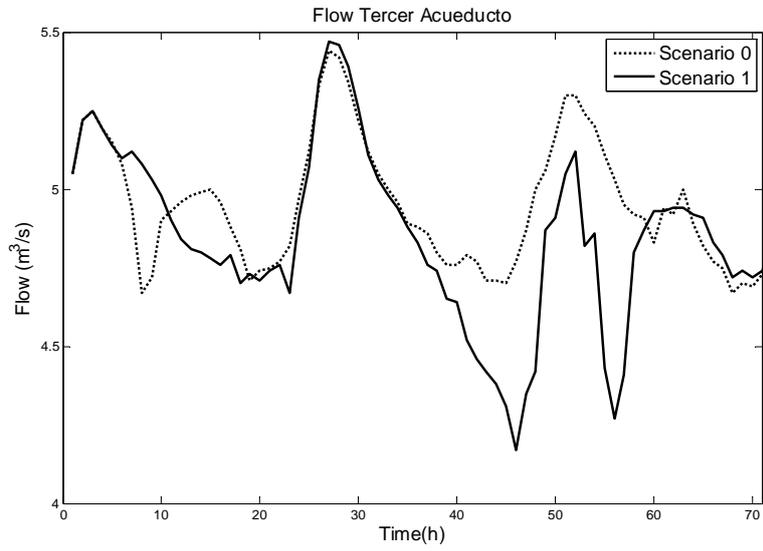
Fig. 5. Flow at Tercer Acueducto
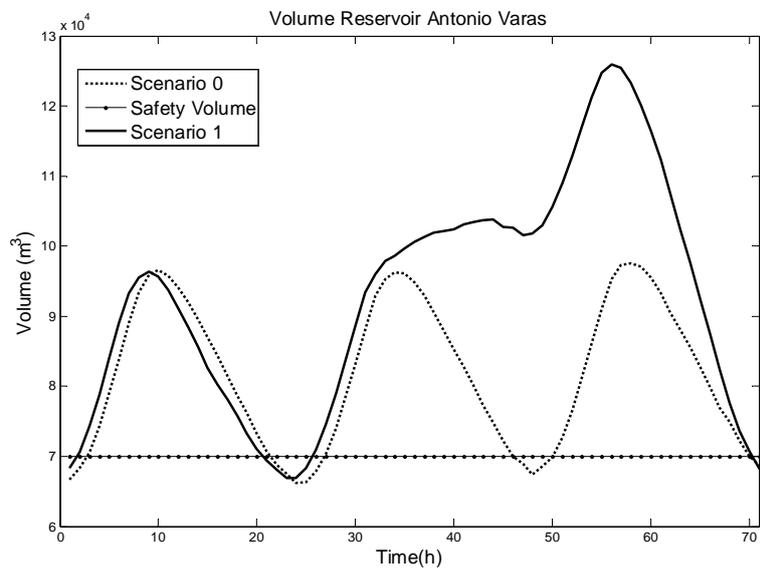
Fig. 6. Volume at the Antonio Varas Reservoir
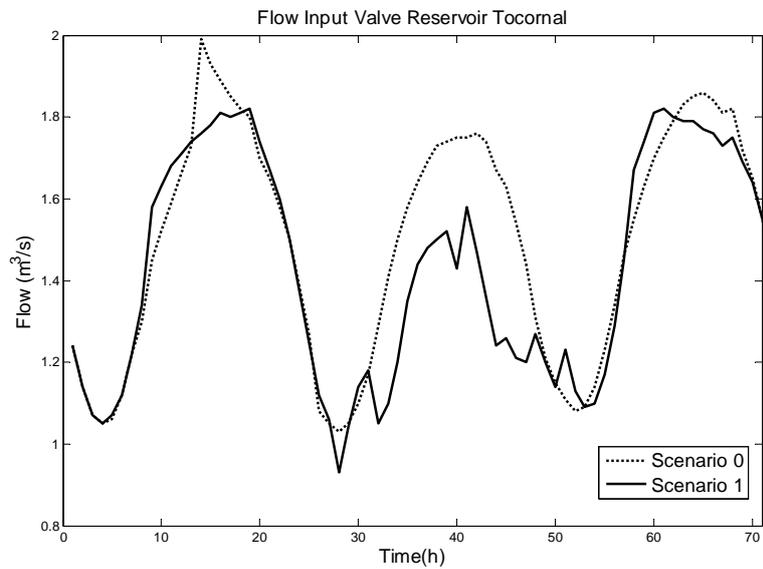
Fig. 7. Flow at the Input Valve of Tocornal Reservoir

6. CONCLUSIONS

This paper has presented a generic tool, named PLIO, that allows to implement the real-time operational control of water networks using predictive optimal control techniques. This tool is able to manage large water systems including reservoirs, open-flow channels for water transport, water treatment plants, pressurized water pipe networks, tanks, flow/pressure control elements and a telemetry/telecontrol system. Predictive optimal control is used to generate flow control strategies from the sources to the consumer areas to meet future demands with appropriate pressure levels, optimizing operational goals such as network safety volumes and flow control stability. PLIO allows to build the network model graphically and then to automatically generate the model equations used by the predictive optimal controller. Additionally, PLIO can work off-line (in simulation) and on-line (in real-time mode). The case study of Santiago-Chile is presented to exemplify the control results obtained using PLIO off-line (in simulation). Now being starting to be applied in Murcia, Barcelona and Almería, all in Spain.

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REFERENCES

Andreu, J., Capilla, J., Sanchís, E. "AQUATOOL, a generalized decision support system for water resources planning and management". Journal of Hydrology, 177, 269–291, 1996. (http://www.iiama.upv.es)

Brdys, M. A., Ulanicki, B. (1994). *Operational control of water systems: Structures, algorithms and applications*. Prentice Hall International, UK.

Brdys, M.A., Grochowski, M., Gminski, T., Konarczak, K., Drewa, M. (2008). "Hierarchical predictive control of integrated wastewater treatment systems". Control Engineering Practice, 16 (6), pp. 751–767.

Bou, V., Martinez, F., Conejos, P. (2006). "SCA-Red: A general purpose SCADA application for taking decision in real time with the aid of a hydraulic model" ASCE, Water Distribution Systems Analysis Symposium, 2006. (http://www.iiama.upv.es)

Bunn, S., Wooley, X. (2001). "DERCETO: An on-line pump schedule optimisation system". New Zealand Water and Wastes Association Annual Conference, 2001. (http://www.derceto.com)

Butler D., Memon, F. A. (2006). *Water Demand Management.* IWA Publishing, London, UK.

Chow, V.T., *Open-channel hydraulics*, New York: McGraw-Hill, 1959.

Camacho, E. F. and Bordons, C. (2004). "Model Predictive Control". Springer, London, UK.

Cembrano, G., Quevedo, J. (1999), *Optimization in Water Networks Computing and Control for the Water Industry* (R. Powell, K. S. Hindi eds.) Research studies Press, UK.

Cembrano, G., Wells G., Quevedo J., Pérez R., Argelaguet R. (2000). "Optimal Control of a Water Distribution Network in a Supervisory Control System". *Control Engineering Practice,* 8(10), 1177-1188. Elsevier. Great Britain.

Diaz, G., Brown, T., Sveinsson, O. (2000). "AQUARIUS: A Modelling System for River Basin Allocation". United States Department of Agriculture, General Technical Report RM-GTR-299.

GAMS (2004) *The Solver Manuals* GAMS. Development Corporation. Washington DC.

Jamielson D., Shamir U., Martinez F., Franchini M. (2007) "Conceptual design of a generic, real-time, near-optimal control system for water distribution networks". Journal of Hydroinformatics, vol. 9 (1), pp. 3-14.

Jeppson R. W. (1983) *Analysis of Flow in Pipe Networks* Ann Arbor Science, 6th Edition, New York.

Johnson, R.W. (1998) The Handbook of fluid dynamics. Boca Raton CRC Press Heildeberg Springer-Verlag

Ljung, L. (1999) "System Identification - Theory For the User", 2nd ed, PTR Prentice Hall, Upper Saddle River, N.J..

Maciejowski, J.M. (2002). *Predictive Control with Constraints*. Ed. Addison-Wesley, Wokingham, UK.

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

Maksimovic C., Butler, D., Memon A. A.. K (2003). *Advances in Water Supply Management*. Swets & Zeitlinger, The Netherlands.

Microsoft Corporation (2002) Windows XP- Guidelines for Applications. http://www.microsoft.com/whdc/hwdev/windowsxp/downloads/default.mspx.

Nitivattananon V., Sadowsky E., Quimpo R. G. (1996) "Optimization of Water Supply System Operation" *Journal of Water Resources Planning and Management ASCE,* 122(5), 374-384.

Ocampo-Martínez, C., Ingimundarson, A., Puig, V., Quevedo, J. (2008). Objective prioritization using lexicographic minimizers for MPC of sewer networks. *IEEE Transactions on Control Systems Technology*, 16(1):113-121.

Quevedo, J., Puig, V., Cembrano, G., Blanch. J. (2010) "Validation and reconstruction of flow meter data in the Barcelona water distribution network". Control Engineering Practice, Volume 18, Issue 6, June, pp. 640-651

Rao, Z. Wicks, J., West. S. (2005). "ENCOMS: An Energy Cost Minimization System for Real-Time, Operational Control for Water Distribution Networks". 8th International Conference on Computing and Control for the Water Industry, University of Exeter, Exeter, U.K., pp. 85–90. (www.halcrow.com).

Shamir, U., Salomons, E. (2008). "Optimal real-time operation of urban water distribution systems using reduced models". *Water Resources Planning and Management*, Vol 134, Issue 2, pp 181-185.

Simon, D. (2006). "Optimal State Estimation: Kalman, H-infinity, and Nonlinear Approaches", John Wiley & Sons.

Tu M., Y., Tsai F. T. C., Yeh W. W.G. (2005): "Optimization of Water Distribution and Water Quality by Hybrid Genetic Algorithm", *Journal of Water Resources Planning and Management*, 131(6), 431-440, ASCE.

Kuzcera, G. (1997). WATHNET: A Generalised Water Supply Headworks Simulation using Network Linear Programming. Department of Civil, Surveying and Environmental Engineering, University of Newcastle, Australia.

Westphal, K. S., Vogel R.M., Kirschen P. and Chapra S.C. (2003) "Decision Support System for Adaptive Water Supply Management", *Journal of Water Resources Planning and Management,* 129(3), 165-177, ASCE.

Yates, D., Sieber, J., Purkey, D. "WEAP21 – A Demand, Priority, and Preference Drivn Water Planning Model. Part I: Model Characteristics". IWRA, Water International, Volume 30, Number 4, December, 2005. (http://www.weap21.org/)