Chapter 12
Model Predictive Control of Water Networks considering Flow

Abstract Water transport networks (WTN) are generally used to convey water from production plants or sources to storage tanks close to the consumptions areas. Tanks are usually built with enough elevation to guarantee the service pressure required for their associated consumption area. WTNs contain large water mains and control elements, such as pumping stations and valves, linking the sources to consumption areas. Their operational control involves planning the control actions at pumping stations and valves ahead in time for periods of 24 to 48 hours, according to demand prediction. Then, the control problem is a resource allocation problem, with costs associated to water acquisition and treatment (production) and to electricity costs of pumping operations. Model predictive control (MPC) techniques are very suitable to perform the real-time operational control of water transport networks, as they can compute, ahead of time, the best admissible control strategies for valves, pumps, or other control elements in a network to meet demands and achieve an operational goal. Typical goals in the management of water transport networks are: minimum energy consumption, cost minimization, service safety, smoothness of control actions, pressure regulation and others. This chapter will show the fundamentals of control oriented modelling in water transport networks and it will be shown, with real case studies that MPC can provide an efficient solution to predictive water resource allocation, which outperforms traditional operational management, improving the above-mentioned operational goals.

12.1 Introduction

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 [26], [16], [12]. 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., [3], [8], [1], [10].

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 [3]). This chapter proposes the use of model predictive control (MPC) techniques to generate flow-control strategies in a transport network, delivering water from the drinking water treatment plants to the consumer areas to meet future demands. Setpoints for pumps and valves are computed by optimizing a performance index expressing operational goals such as economic cost, safety water storage and smoothness in flow control actions. The main point is to highlight the advantages of using optimization-based control techniques, such as MPC, to improve the performance of a water transport network, taking into account their large-scale nature (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.

12.2 Problem statement

12.2.1 Operational control of water networks

Complex nonlinear models are very useful for off-line operations (for instance, calibration and simulation). Detailed mathematical representations such as the pressure-flow models for DWNs allow the simulation of those systems with enough accuracy to observe specific phenomena, useful for design and investment planning. However, for on-line computation purposes such as those related to global management, a simpler and control-oriented model structure must be conveniently selected. This simplified model includes the following features:

(i) Representativeness of the main network dynamics: It must provide an evaluation of the main representative hydrological/hydraulic variables of the network and their response to control actions at the actuators.
(ii) Simplicity, expandability, flexibility and speed: It must use the simplest approach capable of achieving the given purposes, allowing very easily to expand and/or modify the modelled portion of the network.
(iii) Amenability to on-line calibration and optimization: this modelling approach must be easily calibrated on-line using data from the telemetry system and embedded in an optimization problem to achieve the network management objectives.

Figure 12.1, adapted from [23] and [14], shows a hierarchical structure for a real-time control (RTC) water system. There, the MPC, as the global control law, determines the references (set points) for the local controllers placed at different elements

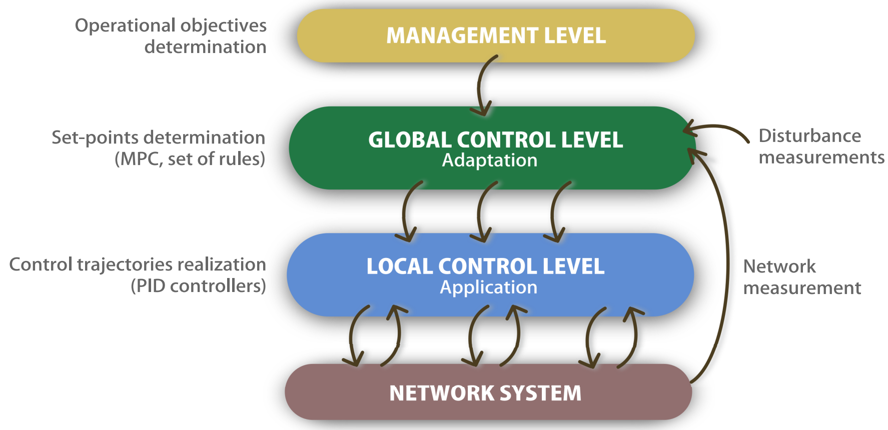

Fig. 12.1 Hierarchical structure for RTC system.

of the networked system. These references are computed according to measurements taken from sensors distributed around the network. The management level provides the MPC with its operational objectives, which are reflected in the controller design as the performance indices to be enhanced, which can be either minimized or maximized, depending on the case. Finally, water systems control requires the use of a supervisory system to monitor the performance of the different control elements in the network (sensors and actuators) and to take appropriate correcting actions in the case where a malfunction is detected, to achieve a proper fault-tolerant control [2].

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. Operators 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 water demand generally presents daily patterns and reasonably good hourly 24-hour-ahead demand predictions may, in general, be available. 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 proposed here is based on demand satisfaction at the transport level, 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.

12.2.2 Operational control of water network using MPC

Water networks are very complex multivariable systems. MPC provides suitable techniques to implement the operational control of water systems to improve their performance, since it allows to compute optimal control strategies ahead in time for all the control elements [5, 13]. 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.

12.3 Proposed approach

The aim of using MPC techniques for controlling DWN is to compute, ahead in time, the input actions to achieve the optimal performance of the network according to a given set of control goals. MPC strategies have some important features to deal with complex systems such as DWNs, namely the amenability to include disturbance forecasts, physical constraints and multivariable system dynamics and objectives in a relatively simple way.

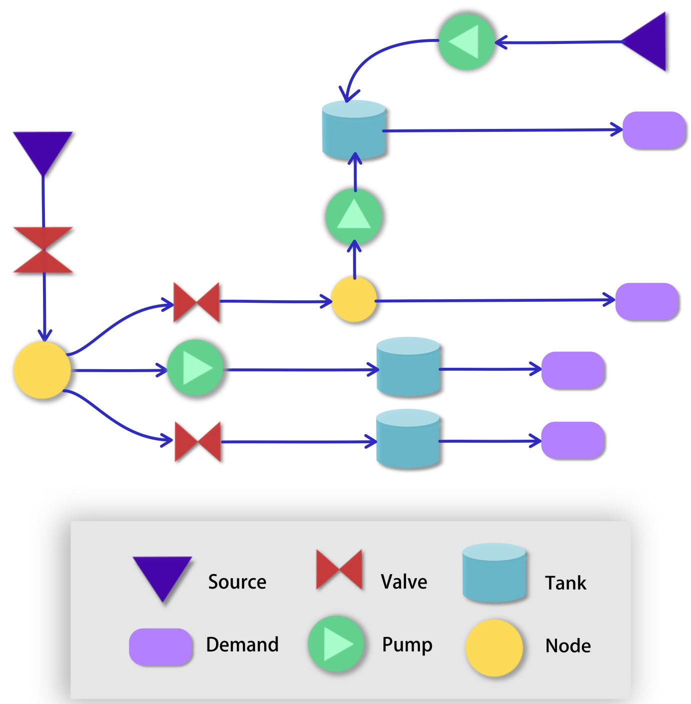

Fig. 12.2 Example of a basic topology of a generic drinking water transport network. Note that the interaction of the main constitutive elements shown here: sources supply water to the system by means of pumps or valves, depending of the nature of the particular source (superficial or underground). Water is moved by using manipulated actuators in order to fill detention tanks and/or supply water to demands sectors.

12.3.1 Modelling

Several modelling techniques dealing with DWNs have been presented in the literature; see, e.g., [3, 15]. Here, a control-oriented modeling approach that considers a flow-model is outlined, which follows the principles presented by the authors in [7, 8] and [19]. The extension to include the pressure-model can be found in Chapter Chapter 13. A DWN generally contains a set of pressurized pipes, water tanks at different elevation, and a number of pumping stations and valves to manage water flows, pressure and elevation in order to supply water to consumers.

The DWN model can be considered as composed of a set of constitutive elements, which are presented and discussed below. Figure 12.2 shows, in a small example, the interconnection of typical constitutive elements.

12.3.1.1 Tanks

Water tanks provide the entire DWN with the storage capacity of drinking water at appropriate elevation levels to ensure adequate water pressure service to consumers. The mass balance expression relating the stored volume v in the n-th tank can be written as the discrete-time difference equation

$$v_n(k+1) = v_n(k) + \Delta t \left(\sum_j q_{\text{in}}^{jn}(k) - \sum_h q_{\text{out}}^{nh}(k) \right), \qquad (12.1)$$

where $q_{\text{in}}^{jn}(k)$ denotes the manipulated inflows from the j-th element to the n-th tank, and $q_{\text{out}}^{nh}(k)$ denotes the manipulated outflows from the n-th tank to the h-th element (which includes the demand flows as outflows). Moreover, Δt corresponds with the sampling time and k the discrete-time instant. The physical constraint related to the range of admissible storage volume in the n-th tank is expressed as

$$v_n^{min} \leq v_n(k) \leq v_n^{max}, \quad \text{for all } k, \qquad (12.2)$$

where v_n^{min} and v_n^{max} denote the minimum and the maximum admissible storage capacity, respectively. Notice that $\underline{v}_n$ might correspond with an empty tank; in practice this value can be set as nonzero in order to maintain an emergency stored volume.

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

12.3.1.2 Actuators

Two types of control actuators are considered: valves and pumps, or more precisely, complex pumping stations. A pumping station generally contains a number of individual pumps with fixed or variable speed. In practice, it is assumed that the flow through a pumping station is a continuous variable in a range of feasible values. The manipulated flows through the actuators represent the manipulated variables, denoted as q_u. Both pumping stations and valves have lower and upper physical limits, which are taken into account as system constraints. As in (12.2), they are expressed as

$$q_{u_m}^{min} \leq q_{u_m}(k) \leq q_{u_m}^{max}, \quad \text{for all } k, \qquad (12.3)$$

where $q_{u_m}^{min}$ and $q_{u_m}^{max}$ denote the minimum and the maximum flow capacity of the m-th actuator, respectively. Since this modelling is stated within a supervisory control framework, it is assumed that a *local controller* is available, which ensures that the required flow through the actuator is obtained.

12.3.1.3 Nodes

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

$$\sum_j q_{\text{in}}^{jr}(k) = \sum_h q_{\text{out}}^{rh}(k), \tag{12.4}$$

where $q_{\text{in}}^{jr}(k)$ denotes inflows from the j-th element to the r-th node, and $q_{\text{out}}^{rh}(k)$ denotes outflows from the r-th node to the h-th element. From now on, node inflows and outflows will be denoted by q_{in} and q_{out}, even if they are manipulated variables (denoted by q_u).

12.3.1.4 Demand Sectors

A demand sector represents the water demand of the network users of a certain physical area. It is considered as a measured disturbance of the system at a given time instant. The demand can be anticipated by forecasting algorithms, which are integrated within the MPC closed-loop architecture. For the cases of study in this chapter, the algorithm proposed in [21], among others discussed in Chapter 6, is considered. This algorithm typically uses a two-level scheme composed of

(i) a time-series model to represent the daily aggregate flow values, and
(ii) a set of different daily flow demand patterns according to the day type to cater for different consumption during the weekends and holidays periods. Every pattern consists of 24-hourly values for each daily pattern.

The 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. Regarding the daily demand forecast, its corresponding flow model is built on the basis of an ARIMA time-series modeling approach described in [20]. Then, the structure of the daily flow model for each demand sensor may be written as

$$\begin{aligned} y_p(k) = &-b_1 y(k-1) - b_2 y(k-2) - b_3 y(k-3) - b_4 y(k-4) \\ &-b_5 y(k-5) - b_6 y(k-6) - b_7 y(k-7), \end{aligned} \tag{12.5}$$

where the parameters $b_1, \ldots, b_7$ are estimated based on historical data. The 1-hour flow model is based on distributing the daily flow prediction provided by the time-series model in (12.5) using an hourly-flow pattern that takes into account the daily/monthly variation as follows:

$$y_{ph}(k+i) = \frac{y_{pat}(k,i)}{\sum_{j=1}^{24} y_{pat}(k,j)} y_p(k), \qquad i = 1,\ldots,24, \tag{12.6}$$

where $y_p(k)$ is the predicted flow for the current day k using (12.5) and $y_{pat}(k)$ is the prediction provided considering the flow pattern class corresponding to the current day. Demand patterns are obtained from statistical analysis.

12.3.2 Control-oriented model

Considering the set of compositional elements described above, the control-oriented model can be obtained by joining those elements and their corresponding dynamic descriptions. In a general form, the expression which collects all these dynamics can be written as the mapping

$$\mathbf{x}(k+1) = \mathbf{g}(\mathbf{x}(k), \mathbf{u}(k), \mathbf{d}(k)), \tag{12.7}$$

where $\mathbf{x} \in \mathbb{X} \subseteq \mathbb{R}^{n_x}$ corresponds to the system states, $\mathbf{u} \in \mathbb{U} \subseteq \mathbb{R}^{n_u}$ denotes the system inputs (manipulated variables) and $\mathbf{d} \in \mathbb{D} \subseteq \mathbb{R}^{n_d}$ denotes the system disturbances. $\mathbf{g} : \mathbb{R}^{n_x} \times \mathbb{R}^{n_u} \times \mathbb{R}^{n_d} \to \mathbb{R}^{n_x}$ is an arbitrary system state function and $k \in \mathbb{Z}_+$.

In the case of DWN, (12.7) is associated to the set of tank expressions in (12.1). Hence, a control-oriented discrete-time state-space model that can be written as [19]

$$\mathbf{x}(k+1) = \mathbf{A}\,\mathbf{x}(k) + \mathbf{B}\,\mathbf{u}(k) + \mathbf{B}_p\,\mathbf{d}(k), \tag{12.8}$$

where, in particular, $\mathbf{x}$ corresponds to the water volumes v of the n_x tanks, $\mathbf{u}$ represents the manipulated flows q_u through the n_u actuators (pumps and valves), and $\mathbf{d}$ corresponds with the vector of n_d water demands (measured disturbances affecting the system). $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{B}_p$ are the system matrices of suitable dimensions. Note that, since the system control-oriented model of a DWN does not collect the static dynamics described by DWN nodes in (12.4), then (12.8) can be further rewritten as

$$\mathbf{x}(k+1) = \mathbf{A}\,\mathbf{x}(k) + \boldsymbol{\Gamma}\,\boldsymbol{\mu}(k), \tag{12.9a}$$

$$\begin{bmatrix} \mathbf{E}_u \; \mathbf{E}_d \end{bmatrix} \boldsymbol{\mu}(k) = 0, \tag{12.9b}$$

where $\boldsymbol{\Gamma} = [\mathbf{B} \quad \mathbf{B}_p]$, $\boldsymbol{\mu}(k) = [\mathbf{u}(k)^T \quad \mathbf{d}(k)^T]^T$, and $\mathbf{E}_u$, $\mathbf{E}_d$ are matrices of suitable dimensions. It can be seen that (16.10a) comes from the mass balance in tanks while (16.10b) comes from the network nodes. Also notice that when all the network flows are manipulated, then $\mathbf{A}$ is an identity matrix of suitable dimensions.

12.3.3 Control criteria

It is possible to use different control objectives depending on the operational goals considered by the network managers. This section describes the most common control objectives and the resultant multi-objective cost function. Therefore, this chapter considers and discussed the following control objectives [17, 19]:

Minimization of water production and transport costs

The main economic costs associated with drinking water production are due to treatment processes, water acquisition or use costs and, most importantly, to electricity costs associated to pumping. Delivering this drinking water to appropriate pressure levels through the network involves important electricity costs in booster pumping as well as elevation from underground devices. In a specific case, this objective can be mathematically formulated as the minimization of

$$J_1(k) \triangleq (\boldsymbol{\alpha}_1 + \boldsymbol{\alpha}_2(k))^T \, \mathbf{u}(k), \tag{12.10}$$

where $\boldsymbol{\alpha}_1$ corresponds to a known vector related to water production costs, depending on the selected water source, and $\boldsymbol{\alpha}_2(k)$ is a vector of suitable dimensions associated to the energy pumping costs. Note the k-dependence of $\boldsymbol{\alpha}_2$ since the pumping cost has different values according to the variable electric tariffs along a day.

Appropriate management of safety water storage

The satisfaction of water demands must be fulfilled at all times. However, some risk prevention mechanisms need to be introduced in the tank management so that, additionally, the stored volume is preferably maintained above certain safety value for eventual emergency needs and to guarantee future water availability. Therefore, this objective may be achieved by minimizing the following expression:

$$J_2(k) = \begin{cases} (\mathbf{x}(k) - \mathbf{x}^{\text{safe}})^T \, (\mathbf{x}(k) - \mathbf{x}^{\text{safe}}) & \text{if} \quad \mathbf{x}(k) \leq \mathbf{x}^{\text{safe}}, \\ 0 & \text{otherwise}, \end{cases} \tag{12.11}$$

where $\mathbf{x}^{\text{safe}}$ is a term which determines the safety volume to be considered for the control law computation. This term might appear as unnecessary given the guarantees of the MPC design but, since a trade-off between the other costs and the volumes is present, the controller would tend to keep the lowest possible the tanks water volumes. This fact would reduce the safety of the system to handle unexpected extra demands, such as fire extinction, among others.

Smoothing of control actions

Valves must also operate smoothly in order to avoid big transients in the pressurized pipes. This fact could lead to poor pipe condition. The use of a smooth reference changes also *helps* the lower-level regulator performance. Similarly, water flows requested from treatment plants must have a smooth profile due to plants operational constraints. To obtain such smoothing effect, control signal variation between consecutive time intervals is therefore penalized. The penalty term to be minimized is

$$J_3(k) = \Delta\mathbf{u}(k)^T\ \Delta\mathbf{u}(k), \tag{12.12}$$

where $\Delta\mathbf{u}(k) \triangleq \mathbf{u}(k) - \mathbf{u}(k-1)$.

Multi-objective performance function

The multi-objective performance function $\mathcal{J}(k)$ that gathers the aforementioned control objectives, either in the case of DWN or SN can be written as

$$\mathcal{J}(k) = \sum_{j=1}^{\varphi} \gamma_j J_j(k), \tag{12.13}$$

where a set of φ control objectives are considered and, in turn, a *multi-objective* open-loop optimization problem (OOP) is stated. The prioritization of the control objectives is performed by using the order of the mathematical cost function associated to each objective, and also a set of appropriate weights γ_j. These weights are selected off-line by means of trial and error procedures, taking into account the priority of each objective within the cost function. More sophisticated tuning methodologies for tuning multiobjective control problems based on lexicographic minimizers [18], goal programming [9], or Pareto-front computations [25] may be also considered.

12.3.4 MPC problem formulation

Collecting the parts described in previous subsections, the MPC design follows the traditional procedures presented in [5, 13, 22], which involve solving an optimization problem over a prediction horizon H_p, where a cost function is minimized subject to a set of physical and operational constraints. Once the minimization is performed, a vector of H_u control actions over H_p is obtained. Only the first component of that vector is considered and applied to the plant. The procedure is repeated for the next time instant taking into account the feedback measurements coming from the system, following the classic receding-horizon strategy.

In general terms, the MPC controller design is based on the solution of a OOP

$$\mathcal{V}(k,H_p) = \min \sum_{i=0}^{H_p} \sum_{j=1}^{\varphi} \gamma_j J_j(k+i|k), \tag{12.14}$$

subject to the system model and the physical and operational constraints, where H_p corresponds to the prediction horizon, and index k represents the current time instant while index i represents the time instant along H_p. Hence, notation $k+i|k$ denotes the time instant $k+i$ given k. Note that (12.14) corresponds with (12.13) over the prediction horizon.

According to the case, the minimum of $\mathcal{V}(k,H_p)$ is achieved by finding a set of optimal variables which generally correspond with the manipulated variables of the system model but that could include further variables of diverse nature. Hence, for a prediction window of length H_p and considering $\mathbf{z} \in \mathbb{R}^{sH_p}$ as the set of s optimization variables for each time instant over H_p, the multi-objective optimization problem can be formulated as

$$\min_{\{\mathbf{z} \in \mathbb{R}^{sH_p}\}} f(\mathbf{z}) \tag{12.15a}$$

subject to

$$H_1(\mathbf{z}) \le 0, \tag{12.15b}$$

$$H_2(\mathbf{z}) = 0, \tag{12.15c}$$

where $f(\mathbf{z})$ comes from the manipulation of (12.14). Moreover, $H_1(\mathbf{z})$ and $H_2(\mathbf{z})$ are vectors of dimensions $r_i H_p \times 1$ and $r_e H_p \times 1$, respectively, containing the constraint functions. Here, r_i is the number of inequality constraints and r_e is the number of the problem equality constraints. It can be observed that (12.15b) and (12.15c) gather all problem constraints including those from the system model, the physical restrictions of its variables and the operational and management constraints.

Assuming that the OOP (12.15) is feasible for $\mathbf{z} \in \mathbb{R}^{sH_p}$, there exists an optimal solution given by the sequence

$$\mathbf{z}^* \triangleq \left(\mathbf{z}^*(0|k), \mathbf{z}^*(1|k), \ldots, \mathbf{z}^*(H_p|k)\right) \tag{12.16}$$

and then the receding horizon philosophy sets [13]

$$\mathbf{z}_{\text{MPC}}(\mathbf{x}(k)) \triangleq \mathbf{z}^*(0|k) \tag{12.17}$$

and disregards the computed inputs from $k = 1$ to $k = H_p$, repeating the whole process at the following time step. Equation (12.17) is known as *the MPC law*.

Therefore, the MPC problem formulation in DWNs gives the expressions for each of the problem parts described above. Thus, mapping (12.7) must be replaced by the system modelling in (16.10) when treating a DWN. Finally, constraints in (12.15b) and (12.15c) are conveniently expressed taking into account the type of network and its constitutive components, for example, constraints in (16.10b) must be included when a DWN is considered. Constraints (12.2) and (12.3) are always included. In order to manage the uncertainty of the system disturbances over the prediction horizon, a suitable approach is the stochastic paradigm, which includes explicit models of uncertainty/disturbances in the design of control laws and by transforming hard constraints into probabilistic constraints. As reviewed in [4], the stochastic approach is a classic one in the field of optimization, a renewed attention has been given to the stochastic programming [24], as a powerful tool for robust control design, leading to the Stochastic MPC and specially to the Chance-Constrained MPC (CC-MPC) [11] (see Chapter Chapter 13).

12.4 Simulations and results

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 WTN are presented. A simulator of this network has been built using MATLAB/SIMULINK and validated using real data coming from real scenarios (see Figures 10 and 11 and the corresponding explanations in Chapter 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 PLIO tool presented in [6] that uses GAMS/CONPOPT solver to solve the corresponding optimization problem. This general-purpose decision support tool has been developed to allow the user to implement optimal/predictive control techniques in large-scale drinking water systems (see Figure 12.3).

The modeling and predictive control problem solution algorithms are designed for real-time decision support, in connection with a SCADA system. The hydraulic modeling relies on simple, but representative enough dynamic equations whose parameters are recalibrated 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 deal with hydraulic uncertainty. This modeling choice, as well as the optimization method selection allows to deal with very large scale systems. Another distinguishing feature is its capability to accommodate complex operational goals.

In Figure 12.4, 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. The model has been validated and accepted by Aguas de Barcelona as representative of the network real behaviour.

The Barcelona WTN is organized in different pressure levels. Figure 12.5 presents the several pressure levels in different colours. Each sector will be supplied through

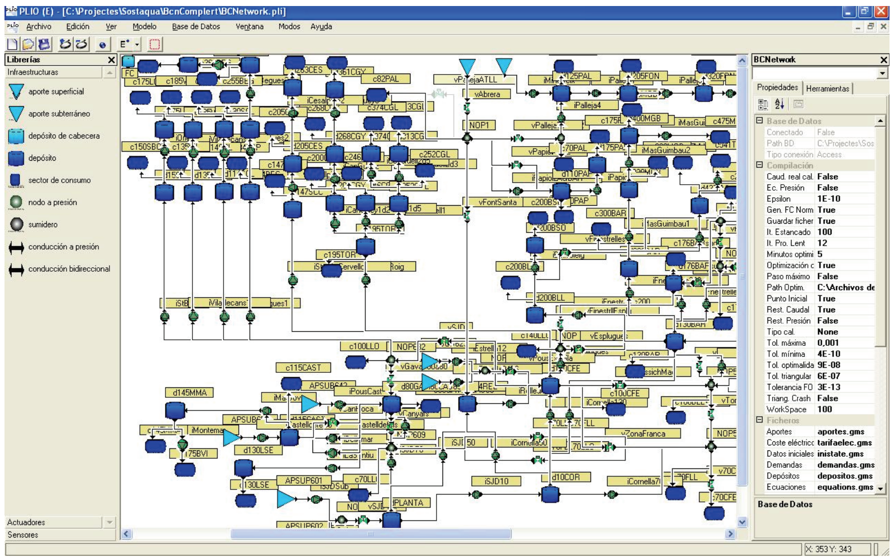

Fig. 12.3 PLIO interface corresponding to the model manager module than allows creating/updating the model of the water network in a user friendly way.

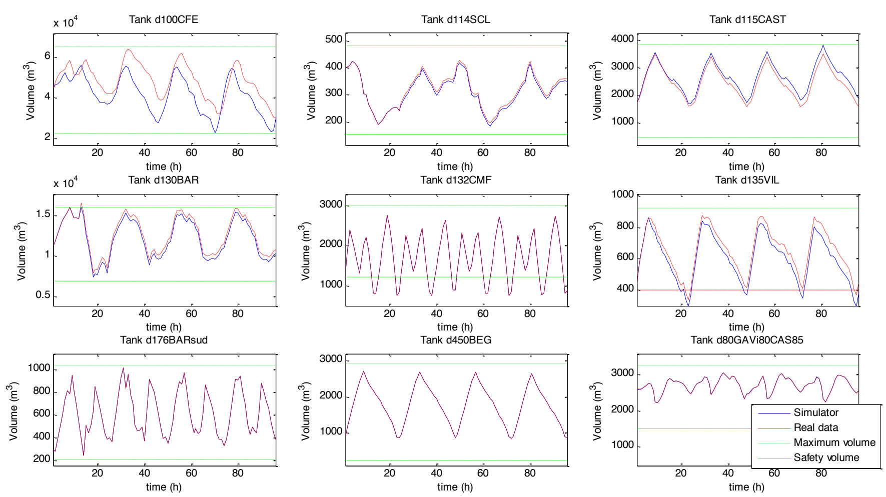

Fig. 12.4 Model validation based on the comparison between real volumes and the simulated ones.

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

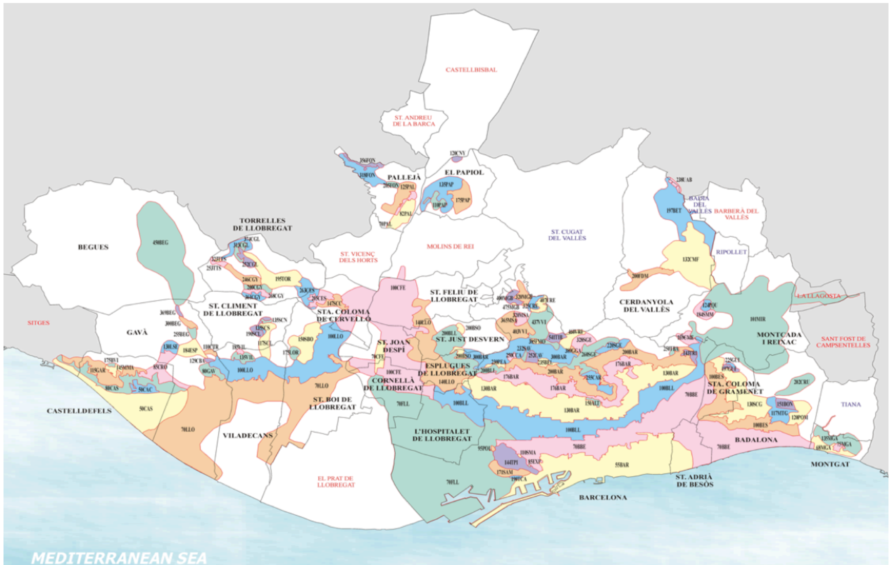

Fig. 12.5 Barcelona Water Network demand sectors.

aggregated demand. Each demand will be modelled using a time series pattern. Figures 12.6 and 12.7 presents the validation of the daily and hourly demand forecast in the sector c176BARsud using the demand forecast algorithm presented in Section 12.3.1.4.

12.4.1 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 objectives of this study are:

- 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:

Scenario 1: Scheduled flow. In this case the flow of all sources is fixed to real values obtained from real historical data.

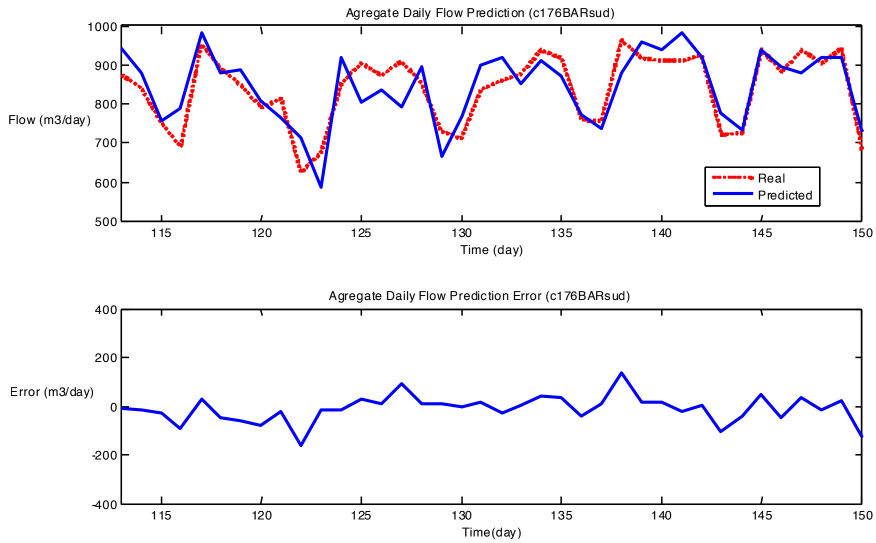

Fig. 12.6 Validation of the aggregate daily demand forecast corresponding to the sector c176BARsud.

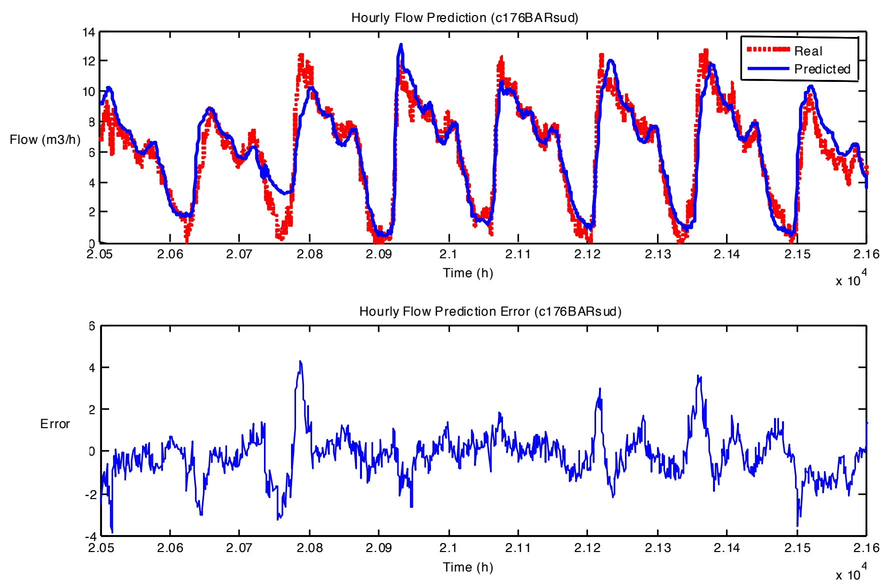

Fig. 12.7 Validation of the hourly demand forecast corresponding to the sector c176BARsud.

Scenario 2: 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.

Table 12.1 Total input volume for studied days.

Date	Total input volume (m^3)	Mean flow (m^3/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

Scenario 3: Fixing main source. The main source of water is fixed while the others are optimized.

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 smoothness factors). Objective function weights are calibrated by experimentally analysing their effects on the compromise between the operational goals, with historic data. In [25], 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 in both scenarios is 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 12.3.1.4 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.

12.4.2 Results and discussion

In all the test scenarios, the MPC controller computed solutions to meet demands and operational constraints at all times, while optimizing the operational goals. Some illustrative results of the MPC application on the complete Barcelona WTN are presented in this section. For these tests the same model is used.

Scenario 1: Scheduled flow

In this first scenario, source flows are imposed using real data obtained from Aguas de Barcelona 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 scenario is used to show the potential of MPC

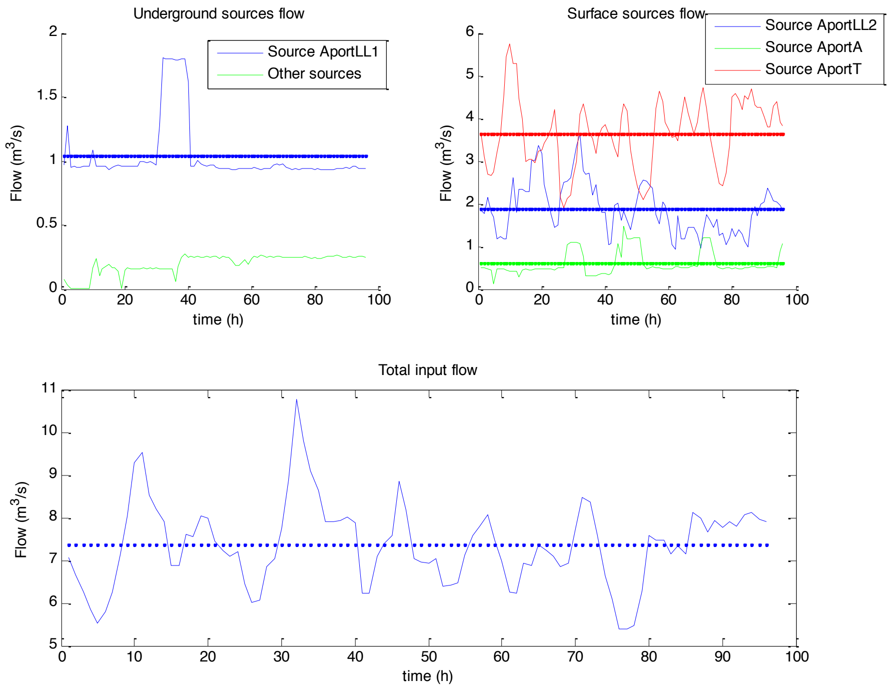

Fig. 12.8 Sources flow evolution for Scenario 1: scheduled flow.

Table 12.2 Current control strategy costs in percentage.

Date	Electricity 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

for minimizing the electrical (pumping) cost. The evolution of source flows is shown in Figure 12.8.

In Table 12.2, electrical and water cost in percentage of the total cost for the current control strategy are shown. In Table 12.3, costs for the MPC control as an increase or decrease percentage with regard to current control are presented.

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

Table 12.3 MPC improvement in percentage for Scenario 1 (scheduled flow) regarding to Table 12.2 values.

Date	Electricity 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

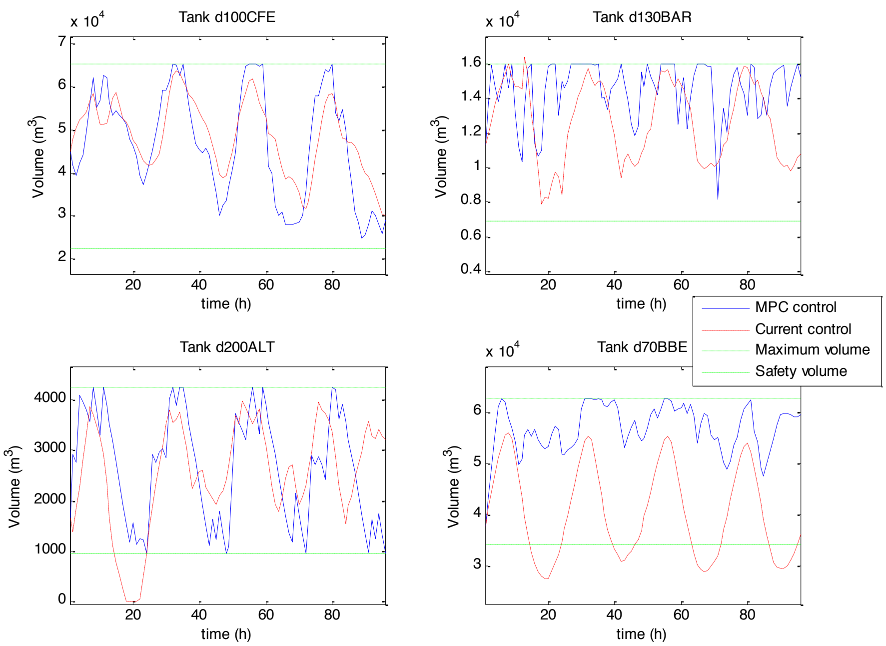

Fig. 12.9 Some tanks volume evolution: current control and MPC control comparison.

and actuators flow plots are shown. In Figure 12.9, some tank volume evolution can be seen, as well as maximum and security volumes.

The smoothness term is not the only factor with effects on pump operation. The electric tariff for each pump is another factor that affects pump operation in order to minimise electrical cost. In Figure 12.10, the effects of the electricity cost 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.

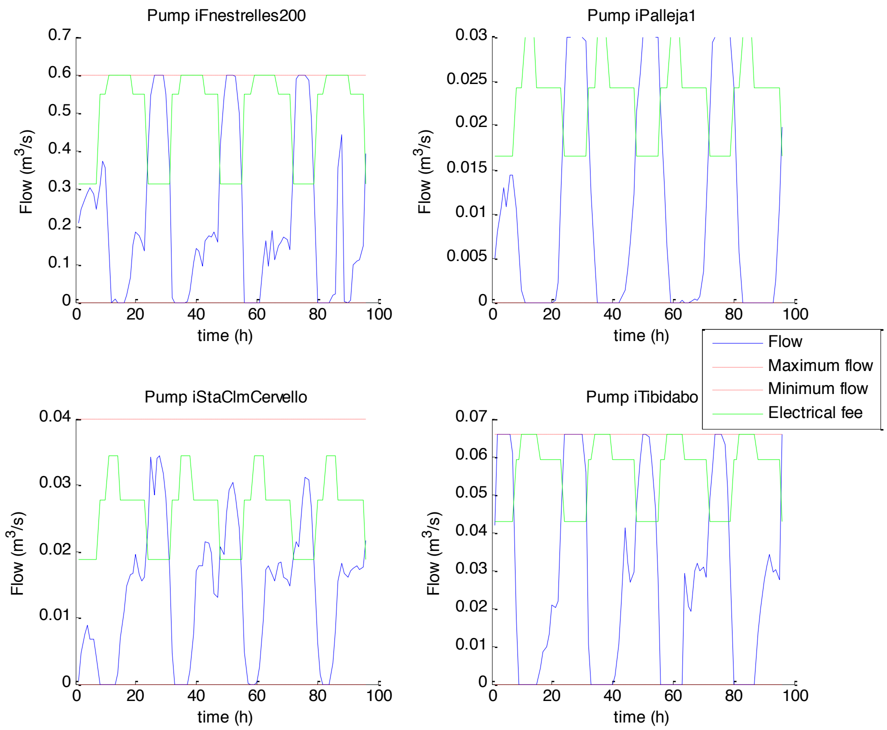

Fig. 12.10 Electrical fee effects on pumps operation.

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 obtain 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 WTN. 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 guarantee 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 12.11, 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.

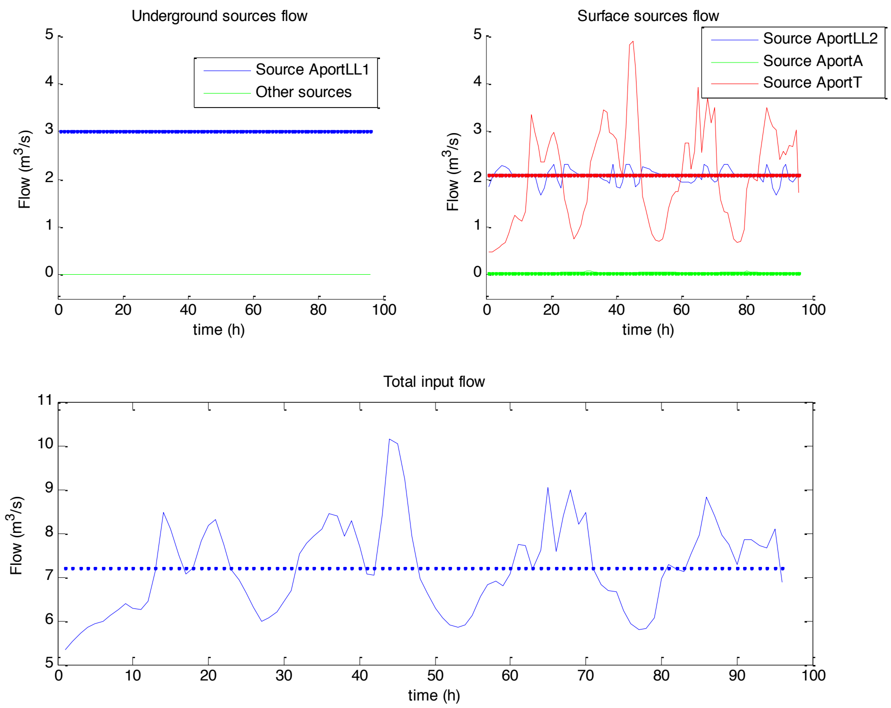

Fig. 12.11 Sources flow evolution for Scenario 2: flow optimization.

Table 12.4 Scenario 2 improvement with regard to current control case (Table 12.2).

Date	Electricity 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

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 12.4 and 12.5 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.

Table 12.5 Scenario 2 improvement with regard to Scenario 1 case (scheduled flow).

Date	Electricity 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

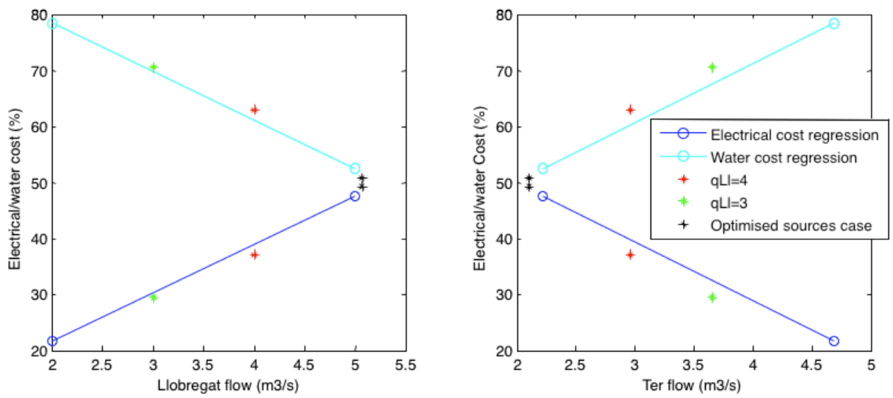

Fig. 12.12 Electrical and water cost when fixing Llobregat source.

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, Aguas de Barcelona 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 12.12, 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 river 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.

Table 12.6 Summary of results for scenarios presented.

Cost	Current control	Scenario 1	Scenario 2
Electrical	32,77%	-18,26%	+21,34%
Water	67,23%	0	-42,90%
Total	100%	-5,94%	-21,96%

12.4.3 Complementary comments

In Table 12.6, a brief summary of results presented is shown, as a mean value of four days of study. The costs of Scenarios 1 and 2 are referred to current control values.

From this table conclusions that can be emphasized are:

- Maximizing the flow from the source Llobregat 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 the contribution from Llobregat.
  – Reduction of water cost involves reduction of Ter source contribution.
  – Total cost is minimised by maximising Llobregat source contribution.

12.5 Conclusions

MPC techniques provide useful tools for generating water management strategies in large and complex water networks, which may be used for decision support, as well as for fully automated control of a water network. This work describes the use of MPC for flow management in a large water system, involving supplies, production plants and water transport into the distribution areas. The chapter 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 chapter 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.

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