Multiobjective Water Pinch Analysis of the Cuernavaca, city Water Distribution Network

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Abstract. Water systems often allow efficient water uses via water reuse and/or recirculation. Defining the network layout connecting water-using processes is a complex problem which involves several criteria to optimize, frequently accomplished using Water Pinch technology, optimizing freshwater flowrates entering the system. In this paper, a multiobjective optimization model considering two criteria is presented: (i)the minimization of freshwater consumption, and (ii) the minimization of the cost of the infrastructure required to build the network that make possible the reduction of freshwater consumption. The optimization model considers water reuse between operations and wastewater treatment as the main optimization mechanism. The operation of the Cuernavaca city water distribution system was analyzed under two different operation strategies considering: leak reduction, operation of wastewater treatment plants as they currently operate, operation of wastewater treatment plants at design capacity, and construction of new infrastructure to treat 100 % of discharged wastewater. Results were obtained with *MDQL* a multiobjective optimization algorithm based on a distributed reinforcement learning framework, and they were validated with mathematical programming.

1 Introduction

Water pinch technology (WPT) evolved out of the broader concept of process integration of materials and energy and the minimization of emissions and wastes in chemical processes. WPT can be seen as a type of mass-exchange integration involving water-using operations, which enables practicing engineers to answer important questions when retrofitting existing facilities and designing new water-using networks. There are three basic tasks in WP: a)Identification of the minimum freshwater consumption and wastewater generation in water-using operations (analysis), b)Water-using network design that achieves the identified flow rate targets for freshwater and wastewater through water reuse, regeneration, and recycle (synthesis), and c)Modify an existing water-using network to maximize water reuse and minimize wastewater generation through effective process changes (retrofit).

Nowadays most WPT problems are formulated as non linear highly restricted programming problems [2]; [14]; [15]. Important efforts have been made in order to make mathematical models more robust and applicable to real situations [1]; [8]; [10].

In general, WPT minimizes freshwater flow rate entering the system, using the mass balance and the contaminants concentrations at the inlet and outlet in all water-using operations as restrictions. Because of the diverse types of water-using operations, treatment effectiveness and cost, and types of contaminants, the criteria for efficient use of water is inherently non linear, multiple and conflicting [1]; [10]; [14]. Some of the criteria that easily arise are: equipment cost minimization, maximization of reliability (amount of contaminant captured in treatment plants), and minimization of wastewater production.

This paper presents a methodology that exploits specific features of the water and wastewater minimization problem. The formulation extends the domain of WPT analysis with elements of capital cost of the required pipe work. Consequently, the optimization is made based on cost efficient networks and networks featuring freshwater consumption. The methodology involves two criteria: the minimization of freshwater consumption and the infrastructure costs. Two techniques are used to solve the multiobjective optimization problem stated for the design of water-using systems: 1) weighted aggregation considering variation in the weight coefficients in order to construct the Pareto set [20], and 2) *MDQL*, which is a heuristic approach based on the exploitation of the knowledge generated during the search process.

The proposed multiobjective optimization model was applied for the case of the water distribution network in the city of Cuernavaca. An operation analysis considering two different strategies was performed: 1) reduction of leaks in the network and operation of wastewater treatment plants as they currently operate, and 2) reduction of leaks in the network, operation of wastewater treatment plants at their design capacity, and construction of new treatment infrastructure to reach 100 % wastewater treatment.

Section two presents the mathematical formulation for the bi-objective optimization problem and its description. In section three the function aggregation method and the MDQL heuristic approach are described. Section four describes the application case. Section five contains a discussion on the obtained results, general conclusions and future research directions.

2 Mathematical formulation

The mathematical model describing a water demanding process considers two main components: a) freshwater sources available to satisfy demands, and b) water-using operations described by loads of contaminants and concentration levels. A case with two sources and two operations is sketched in Figure 1. The design task is to find the network configuration that minimizes the overall demand for freshwater, $\sum f_i$, (and consequently reduce wastewater volume $\sum W_i$) compatible with minimum investment cost. In order to complete the design task the optimization problem is stated in terms of low freshwater consumption, a suitable network topology for water reuse, $X_{i,j}$, and low investment cost. Also, water treatment through treatment plants (TP) is considered, $X_{R,i}$, as a unitary operation, so other operation can reuse water from TP, $X_{i,R}$.

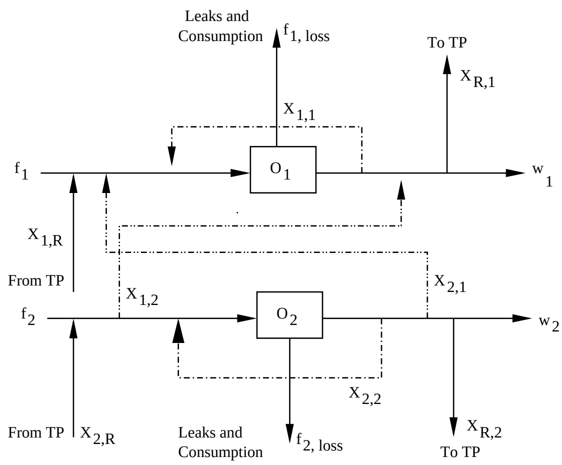

Fig. 1. Block diagram of a water-using system with one two sources and two operations

Unitary operations demanded water, O_i, are defined through their contaminant loads, required flow rates and allowable minimal and maximal contaminant concentrations at influxes and discharges.

Objective functions for freshwater consumption minimization and for infrastructure cost minimization are represented by Equations 1 and 2.

$$MinZ_1 = F_1 = \sum_j cst_j + TPC, \tag{1}$$

$$MinZ_2 = F_2 = \sum_i f_i \tag{2}$$

Where: F_1 is the total cost of the distribution network considering the connection of freshwater sources to unitary operations receiving water directly, and the connection for reusing water between unitary operations. The total distribution network cost is composed by the sum of the partial costs, cst_j, of the pipe segments used for connecting freshwater sources to unitary operations and unitary operations to unitary operations, and TPC (the treatment plant construction cost that applies only for new treatment infrastructure).

F_2, is the total freshwater demanded by the system, obtained by the partial demands of freshwater from each of the unitary operations in the system. Partial demands from unitary operations, say operation O_i, are represented as, f_i. That is f_i is the partial freshwater demand of operation O_i.

2.1 Infrastructure cost

Evaluation of the first objective function, F_1, depends only on the pipe segment costs in the network.These costs are represented as cst_j, (see Equation 3) and depend on three variables: a) pipe length, L_j; b) cost per unit length, PC_j; which depends on the pipe diameter required to transport the demanded flow of water, D_j; and c) a cost factor, CF_j, related to pipe materials required to resist corrosive effects of contaminants. It is important to note that one of the objectives of this work is to demonstrate the benefits obtained by the solution of the multiobjective approach, compared with those obtained with the single objective approach. It is for this reason that some considerations regarding the hydraulic behavior of the network are not included.

$$cst_j = L_j \times PC_j \times CF_j \tag{3}$$

As mentioned in the previous paragraph, the variable PC_j depends on the pipe diameter, $D_j = f(Q_j)$, which is obtained calculating the minimum diameter required to transport the water flow through the pipe. The minimum diameter, D_{min_j}, is obtained through Equation 4; deduced from the definition of flow ($Q = velocity/area$) considering maximum velocities of water in pipes of 2.5 m/s. D_{min_j} is approximated to the closest mayor commercial diameter. Table 1-*(b)* shows diameters and cost per unit length for commercial pipes considered in this work. The data in Table 1 is only demonstrative and can be substituted with real data from local markets.

$$D_{min} = 0.714\sqrt{Q} \tag{4}$$

where: D_{min} is the minimal pipe diameter in mm required to transport flow rate Q ; $Q \in \{f_i, X_{i,j}, W_i\} \forall i, j$ and is given in m^3/s.

In a similar manner, the factor CF_j is related to the capacity of pipe segments to resist corrosive effects due to the presence of contaminants in water flows. Values for the CF_j factor are included in Table 1-*(a)*, calculated considering local prices in Mexico for non corrosive pipes.

Finally the treatment plant construction cost considered in this work is 10 $\$/l$, that is the construction cost in monetary units per liter of treatment capacity for the plant or plants.

2.2 Freshwater demand

To guarantee steady state conditions in the system, it is necessary to restrict the objective functions by the mass balance between unitary operations,and by the maximum and minimum allowed contaminant concentrations on the influxes and discharges of operations [15].

Table 1. Cost factors for pipes resistant to abrasive effects of contaminants *(a)* and cost per unit length for commercial diameter pipes *(b)*

(a)

Contaminant concentration (mg/l)	CF
$0 \leq c \leq 50$	1.25
$50 < c \leq 100$	2.0
$100 < c \leq 150$	2.0
$150 < c \leq 200$	3.0
$200 < c \leq 500$	5.0
$500 < c$	10.0

(b)

Diameter (mm)	PC $\$/m$
99	4.8
150	5.0
200	8.9
250	12.9
300	17.7
350	23.6
400	25.6
450	34.1
500	40.9
610	42.6
762	45.9
838	54.6
$1,016$	69.9
$1,118$	83
$1,219$	94
$1,372$	110

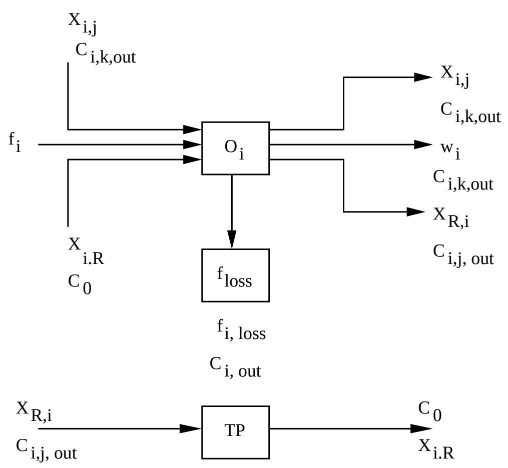

Fig. 2. General structure

The flowrate required in each unitary operation is related to the mass load of contaminants ($\Delta m_{i,k,tot}$) discharged by operations. This is described in Equation 5.

$$f_i = max_c \frac{\Delta m_{i,k,tot}}{c^{max}_{i,k,out} - c^{max}_{i,k,in}} \tag{5}$$

where f_i is the freshwater flow rate for operation O_i; $\Delta m_{i,k,tot}$ is the total mass transfer for each contaminant, k, to the water used at operation O_i (this term is also known as contaminant mass charge [3] and is expressed in kg/h); $c^{max}_{i,k,out}$ and $c^{max}_{i,k,in}$ are the maximum allowed concentration of contaminant k on the discharge and influx of operation O_i, in mg/l respectively.

The optimization model depends on the mass balance between all inlets and all outlets of water to the operation O_i. According to Figure 2, the expression for the mass balance has the form shown in Equation 6.

$$f_i + \sum_{j \neq i} X_{i,j} + X_{i,R} - f_{i,loss} - W_i - \sum_{j \neq i} X_{j,i} - X_{R,j} = 0 \tag{6}$$

where, $X_{i,j}$ is the reusable water flow rate from other operations, say O_j, in operation O_i; $X_{i,R}$ is the treated water from the wastewater treatment plants that can be used in operation O_i; $f_{i,loss}$ is the portion considered as water loss in the operation or water consumption by the operation; W_i is the wastewater flow rate from operation O_i; $X_{j,i}$ is the reusable water flow rate from operation O_i in operations O_j; and $X_{R,i}$ is the portion of the discharged water from operation O_i that receive treatment. All flowrates are represented in m^3/h.

Several (k) different contaminants can be considered in the optimization model. This consideration requires the definition of constraints to restrict the concentration of contaminants at the inlets and outlets of operations, in order to guarantee that water influxes will not affect the operation performance, and to avoid the violation of environmental or operation standards. The satisfaction of this constraints will determine the quantities of fresh and reused water to supply to operations. Contaminant concentration constraint at the influx of the i^{th} operation, $c_{i,k,in}$ is defined by Equation 7.

$$c_{i,k,in} = \frac{\sum_{j \neq i} X_{i,j} c_{j,k,out} + c_{k,0} X_{i,R} - f_{i,loss} c^{max}_{i,k,in}}{\sum_{j \neq i} X_{i,j} + f_i + X_{i,R} - f_{i,loss}} \leq c^{max}_{i,k,in} \tag{7}$$

where, $c_{i,k,in}$ is the concentration of contaminant k at the influx of operation O_i; $c_{j,k,out}$ is the concentration of contaminant, k, at the discharge of operation O_j, $c_{k,0}$ is the concentration of contaminant k in the treated water, $c_{i,k,in}$ is the maximum allowable concentration of contaminant k at the influx of operation O_i. Concentrations are expressed in mg/l.

The same way, contaminant concentration constraint at the outlet of j^{th} operation, $c_{j,k,out}$ is defined by Equation 8.

$$c_{j,k,out} = c_{i,k,in} + \frac{\Delta m_{i,k,tot}}{\sum_{j \neq i} X_{i,j} + f_i + X_{i,R} - f_{i,loss}} \leq c^{max}_{i,k,out} \tag{8}$$

Finally, non negativity constraints are established according to the following equations.

$$
\begin{aligned}
X_{i,j} &\geq 0; \\
f_i &\geq 0; \\
L_j \times PC_j \times CF_j &\geq 0.
\end{aligned}
$$

3 Solution method

For multiobjective optimization problems there is not a single solution, but a set of non dominated solutions (*Pareto-set*), such that the quality of a solution can be improved with respect to a single criterion only by becoming worse with respect to at least one other criterion [4].

In this sense we propose the use of two techniques especially designed to solve optimization problems with more than one criterion. The first, uses an aggregated function constructed with the use of weight coefficients representing the relative importance of the two objective functions. The resulting optimization problem is solved by the reduced gradient method in order to avoid penalty parameters [5] for five combinations of weights to construct the Pareto set. The second approach is an heuristic based on the solution of Markov decision processes known as *MDQL* [17]. MDQL is capable of exploiting the knowledge acquired during the solution process, and has been tested on several benchmark problems showing good performance [17], [19] and more recently [20].

3.1 Aggregated function

This approach is probably the most known and simplest way to solve this type of problems. Some of the first references on it are [12] and [26]. The main idea behind this approach is the construction of a weighted function resulting from the combination of the m objective functions with the use of weight coefficients. The weighted function is then used on a single objective optimization problem. In general terms it is proposed that the weight coefficients, p_i, to be real values such that $p_i \geq 0 \forall i = 1, \ldots, m$. It is also recommended to use normalized weight coefficients, so $\sum_{i=1}^{m} p_i = 1$. More precisely, the multiobjective optimization problem is transformed to the problem stated in Equation 9, which will be called in the successive the "weighted problem".

$$min \sum_{i=1}^{m} p_i \cdot F_i \tag{9}$$

where, $p_i \geq 0 \forall i = 1 \ldots, k$ and $\sum_{i=1}^{k} p_i = 1$.

This approach guarantees the optimality of the Pareto set if the weighted coefficients are positive or the solution is unique [13] [21]. Pareto set construction is made with the variation of the weight coefficients values, solving the weighted problem as many times as the number of variations of the weight coefficients can be configured.

The resulting problem after the application of the weighted aggregation approach to the two objective functions presented in section 2, takes the form presented in Equation 10.

$$F = p_1 \sum_i f_i + p_2 (\sum_j cst_j + TPC) \tag{10}$$

Solution of the weighted problem in Equation 10 is made through the reduced gradient method with the use of the GAMS/MINOS program [11]. Weight coefficients combinations used (p_1, p_2) are: $(0.1, 0.9)$, $(0.25, 0.75)$, $(0.5, 0.5)$, $(0.25, 0.75)$ and $(0.9, 0.1)$.

3.2 Multiple Objective Distributed Q-Learning(MDQL)

In order to efficiently solve optimization problems with more than one objective function it is desirable to use population based approaches, that is, approaches with the capability to generate more than one solution concurrently. Moreover, it is necessary to apply the dominance optimality criterion to evaluate the generated solutions. This is the main hypothesis of much of the recently developed approaches designed to efficiently solve multiobjective optimization problems based on evolutionary computation. Taking advantage of some of the characteristics of evolutionary approaches, it has been previously established that optimization problems can be solved considering search processes as a Markovian decision process [9]. Furthermore successful application of reinforcement learning to multiobjective optimization problems was first presented in [16]; extended and improved in [17] and [19].

MDQL considers a group of agents searching a terminal state, s_t, in an environment formed by a set of states, $\mathcal{S}$. The set of states, or environment, is constructed dividing variable ranges in the parameter space in fixed number of parts, considering that all decision variables can be discretized in a finite number of divisions. Minimum and maximum limits for divisions are considered states, as illustrated in Figure 3. An environment with these characteristics allows to the agents to propose values for each one of the decision variables in the problem.

For each state, $s \in \mathcal{S}$, a set of actions, $\mathcal{A}_s$, is settled, see Figure 3. All actions in states, $a \in \mathcal{A}_s$ have an associated value function, $Q(s, a)$, indicating the goodness of the action to complete a task.

The search mechanism for an agent in MDQL operates when an agent located in a state selects an action based on its value function, $Q(s, a)$. Most of the time the agent selects the best evaluated action (the action with the higher estimated value for $Q(s, a)$), and occasionally a random action with a probability $\epsilon \approx 0$. Action value functions are updated depending on how useful an action can be to an agent to reach a terminal state. This behavior is adjusted with the help of a reward value, $r \in \Re$, and the value function for the best evaluated action in

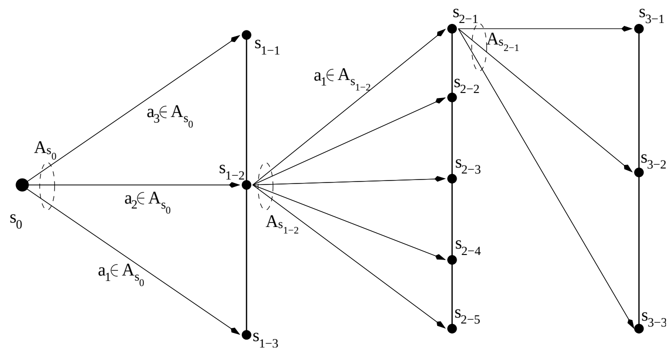

Fig. 3. Variable space division for MDQL

the future state reached by the agent after the execution of the selected action, $Q(s', a')$. This update rule is expressed in Equation 11.

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[r + \gamma \max_{a' \in \mathcal{A}'_s} Q(s',a') - Q(s,a) \right] \tag{11}$$

where $Q(s,a)$ is the value function for the action, $(0 \leq \alpha \leq 1)$ is the learning step ,$(0 \leq \gamma \leq 1)$ is a discount parameter r is an arbitrary reward value, $r \in \Re$, s' and a' are the next state and the best evaluated action for s' respectively .

As an agent explores the state space, $Q(s,a)$ estimations improve gradually, and, eventually, each $\max_{a' \in \mathcal{A}'_s} Q(s',a')$ approaches: $E\left\{\sum_{n=1}^{\infty} \gamma^{n-1} r_{t+n}\right\}$ [23]. Here r_t is the reward received at time t due the action chosen at time $t-1$. Watkins and Dayan [25] have shown that this Q-learning algorithm converges to an optimal decision policy for a finite Markov decision process.

In *MDQL* there is a group of agents, instead of a single agent, interacting with the environment described above, and since the task for the agents is the construction of the Pareto set, the original *Q-Learning* [25] algorithm must be adapted. Main adaptations considered in *MDQL* are listed below.

- Decision variables in the environment have a predefined order, as illustrated in 3, the agents move in the decision variables space obeying this order, so the definition of the values for the decision variables is made in the same order by all the agents.
- A 'map' is constructed with a copy of the action values for each of the available environments (one for each of the solutions in the Pareto set, and solutions violating constraints).
- When all the agents finish a solution (define values for all the decision variables), all solutions are evaluated using the Pareto dominance criterion. Environments for non dominated solutions and solutions that violate any constraint remain in memory to be used in future episodes (see previous item).
- Agents are assigned randomly to the environments in memory.
- Action values update is made in two stages. The first is when agents make a transition using the 'map' of the environment (copy of action value functions)

in which all agents working in the sane environment show their experience updating value functions [18]. Action values update is made considering the following criteria: (i) non dominated solutions receive a positive reward and (ii) solutions violating any constraint receive a punish, calculated as a function of the magnitude of the violated constraints [17] and [19]. Finally, the original action (those used to construct 'map's) value functions are updated considering the same criteria (second stage), 'maps' are destroyed and new solutions incorporated.

Reported Pareto fronts obtained with $MDQL$ are the best after ten executions of the algorithms with the same execution parameters.

4 Cuernavaca city water distribution system, México

Water uses are classified in five categories [7]. Table 2 includes the values for the freshwater demand by each of the operations. It is relevant to note that part of the demanded water is consumed by the operation itself, other part can not be register and is considered as a loss caused by leaks occurring along distribution systems which is about 43.41% [22]. The rest is declared as wastewater and supposedly is discharged with the effluents to the receiving water bodies, in this case the Apatlaco river.

Two contaminants indexes are considered, five day biochemical oxygen demand (BOD_5) and total suspended solids (TSS). Wastewater treatment plants treat 339.15 l/s to BOD_5 and TTS mean concentration of 50 mg/l according to the data reported in the literature [3].

Values for both water quality indexes, $c^{max}_{i,k,out}$, were established using the information obtained from some studies performed to evaluate the degree of contamination in the Apatlaco river [6]. For both contaminants, the concentration in the freshwater supplied to the system is considered to be zero, see Table 2.

Table 2. Freshwater demand and inflow and outflow limit concentration for all operations. Current situation for Cuernavaca city.

Operation O	**Water demand**	BOD_5			TSS		
	f_i	$c^{max}_{i,A,in}$	$c^{max}_{i,A,out}$	$\Delta m_{i,tot}$	$c^{max}_{i,B,in}$	$c^{max}_{i,B,out}$	$\Delta m_{i,tot}$
	l/s	mg/l	mg/l	kg/h	mg/l	mg/l	kg/h
Urban & Public	3,003	0.00	220.00	1,767.74	0.00	220.00	1,403.07
Services	16.19	0.00	220.00	9.53	0.00	200.00	7.56
Agriculture	593.0	50.00	350.00	449.57	50.00	300.00	449.57
Multiple	2.24	0.00	220.00	1.32	0.00	220.00	1.05
Industrial	47.58	0.00	874.00	85.57	0.00	371.00	36.32
Self Service	1.36	0.00	220.00	0.60	0.00	240.00	0.73

There are 15 wastewater treatment plants in Cuernavaca city, ten for the treatment of municipal wastewater and five for the treatment of industrial wastewater. The total treated wastewater flowrate is 364.15 l/s (339.65 municipal and 24.50 industrial [6]. In general the 10 municipal wastewater treatment plants operate at 66.35% of their design capacity and the five industrial wastewater treatment plants at 71.01% of their design capacity.

In order to verify how the system performance can be improved two different strategies were evaluated. The first is the operation of the treatment plants at their current operation capacity, that is 339.65 l/s, and the reduction of leaks in the distribution from 43% to 25%. The second strategy considers the operation of the existing treatment plants at their design capacity, 511.86 l/s, a leak reduction program to decrease the non accounted water from 43% to 25%, and the construction of new treatment facilities to reach 100% of treatment covering. *MDQL* operation parameters used for all test cases were: $\alpha = 0.1$, $\gamma = 0.01$, $r = 1$ for non dominated solutions and $r = -1$ for solutions violating constraints. Otherwise, for both problems decision variables are: six fresh water flow rates, f_i; reusable water flow rate in each operation including treatment plants, $X_{i,j}$, and waste water flow rates, W_i. Each variable discreticized to have increments of 0.1 l/s. Computational cost is $O(k^2)$, being k the number of agents in the problem and is related with the number of objective functions evaluations. More detail can be consulted in [19].

4.1 Results for the first strategy

In this strategy leaks reduction from 43%to 25% and operation of treatment plants keeped in their current operation levels are considered (339.65 l/s).

Results are presented in Figure 4 (left). Since the agriculture is the most demanding operation in Cuernavaca city, the main change in the operation of the Cuernavaca city water distribution network is that water supplied for the agriculture can be supplied from three different sources: the wastewater treatment plants, freshwater and wastewater from the urban and public sector, saving water that cab be used to: a) increment of the irrigated area , and/or b) reduction of freshwater sources exploitation with a benefit to the environment.

The upper left most solution in Figure 4 (left) has a total demanded freshwater flowrate $2,752.6$ l/s, compared with the current demand which represents a decrement of approximately 24.87 %, that is, 911.57 l/s of the amount of water taken from the sources. Freshwater savings represent approximately 28.74 millions of m^3 per year that could increase water availability in Cuernavaca valley aquifer from eight millions of cubic meters to 36.74 millions of cubic meters.

4.2 Results for the second strategy

The second operation analysis strategy considers the operation of existing wastewater treatment plants to their design capacity, leak reduction to 25 %, and construction of new treatment facilities.

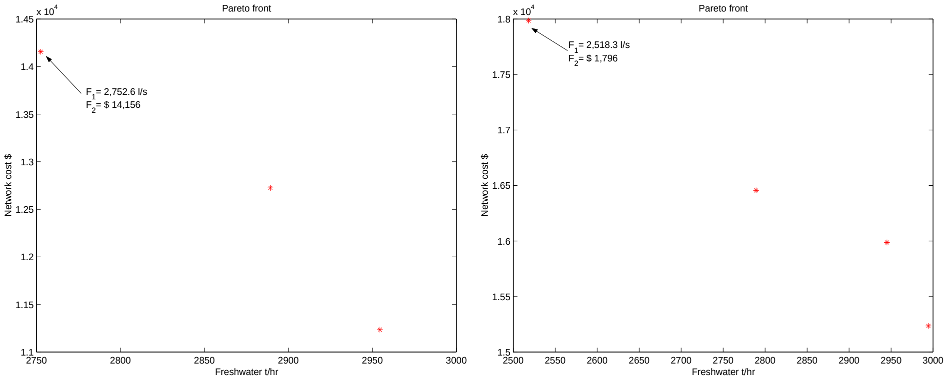

Fig. 4. Cuernavaca city distribution system results for the first strategy (left) and second strategy (right) both Pareto fronts obtained with MDQL

The Pareto front obtained for this test case is presented in Figure 4 (right). The upper left solution with the lowest freshwater demand of $2,581.3\ l/s$ and cost of $\$1,796$ requires the construction of two new wastewater treatment plants. The first with a capacity to treat $81.38\ l/s$ configured to receive 4.6 % of the discharged wastewater from the urban and public sector, and 53 % of the discharged water by multiple sector. The second proposed wastewater treatment plant capacity is $1,130.44\ l/s$ and could receive the 95.4 % resting discarged wastewater by the urban and public sector.

Similar to the results found with the first strategy, demanded water by agriculture is satisfied with the total of the municipal treated water, and with 81.38 l/s coming from the new plant proposed in the design. Industrial water is treated independently from the existing industrial treatment plants.

Water savings arise since a considerable flow of freshwater is not longer supplied to the agriculture sector. Freshwater savings represent 34.15 millions of cubic meters per year, savings that could represent an increment in the freshwater availability of the aquifer from eight to 44.13 millions of cubic meters per year.

As can be also appreciated in Figure 4 (right) that the upper left solution is the lowest freshwater flowrate demand solution, compared with Pareto solution found with the two strategies analyzed. It is also true that Pareto solutions cost are the highest but, at least intuitively, solutions into this Pareto set are more efficient solutions since all discharged water by the Cuernavaca city water distribution system is treated and contamination levels are the lowest. Qualitative efficiency is measured in terms of the remaining contaminant concentration in discharged wastewater to the reception bodies, this parameter is not included in the optimization model, but according to the environmental standards (included in the model) solutions for both strategies are feasible and do not violate them.

4.3 Function aggregation comparison

Figure 5 is a comparison of Pareto fronts obtained with the two strategies evaluated the Cuernavaca city water distribution network. This figure also includes five solutions for the two strategies obtained with the function aggregation and reduced gradient approach. Pareto fronts obtained with *MDQL* and mathematical programming are close to the two analyzed strategies, so it can be said that the obtained results are valid and can be used to make decisions over the real-world problem stated in this paper. It also can be appreciated from Figure 5 that solutions on the extremes of the Pareto fronts are similar, presumably because that solutions correspond to the end extremes of the Pareto fronts for the mathematical model.

This conjecture can be enlarged with the comparison of the solution on the upper left corner in Figure 5 (second strategy) ($2,518\ l/s$) with the solution for the same strategy, but with the sole criterion of freshwater minimization (ideal vector) presented in [3], for which the total demanded freshwater flowrate was $2,586.96\ l/s$. The difference between the single objective and the bi objective solutions can be partially attributed to the weight factors used in the bi objective optimization. This comparison permits the validation of *MDQL* for the solution of the bi-objective optimization model for the design of water using systems presented in this paper, considering the convergence properties of the function aggregation approach [21] and previous results on similar problems [20].

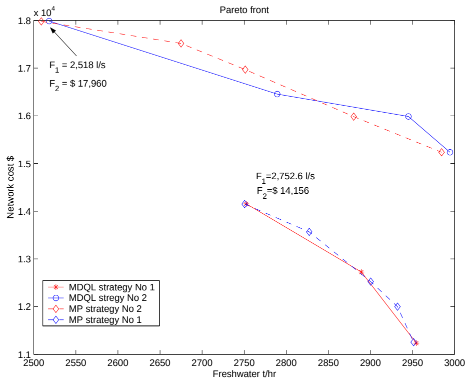

Fig. 5. Comparison of the Pareto fronts obtained for the two strategies evaluated to perform the Cuernavaca city distribution system operation

5 Conclusions

A water pinch optimization model that considers more than one criteria was presented. The model considers the reuse of wastewater from operations, wastewater treatment, consumption flowrates and leaks in the system, and the combination of this mechanisms for the optimization of two objective functions. The reduction of freshwater demands is possible with the guarantee that the quality of the water served to the different users do not violate ecological and sanitary norms. The bi-objective optimization model operates considering mass balances between operations, freshwater sources, wastewater treatment plants, and wastewater disposal effluents. Contaminants loads from operations to water flows are restricted by environmental and operational constraints, resulting in a highly non linear model.

Model solution permits the verification of its behavior, consistency and completeness [20]. Mathematical programming for the solution of a weighted aggregated function of criteria was used as a mean of comparison, selected on the basis of previous results and convergence properties reported in the literature [21]. The objectives of this work were completely satisfied, it can be said that proposed model is complete and represents the behavior of real water distribution systems as the Cuernavaca city distribution system.

The quality, number, and distributions of solutions along the Pareto fronts obtained with *MDQL* seems better compared with the those obtained with mathematical programming. The main difference is that *MDQL* solutions were obtained on a single run without the definition of weight coefficients. So, based on this analysis it can be said that *MDQL* is more competitive, especially because the quality of solutions (approximation of the Pareto front). It is also possible to note that combination of weight coefficients is, sometimes a tedious work decision makers are not totally convinced to do, especially for the preferences definition.

Solution for water pinch problems represent important technical challenges that are only partially solved in the industry. Results presented here can help as a sample of how real applications may be solved with the participation of multidisciplinary teams involving researches from different communities, as in this case.

Finally it is important to say that more work can be made with the optimization model. In this order of ideas constraints implementation to optimize the processes is one of the future activities, this implementation could help in the selection of more efficient processes, for example if wastewater treatment technology is selected in terms of the type of contaminants, the mass remotion could be made more effective and the system more efficient if the proper process is selected and optimized in terms of cost and efficiency. Another important aspect to implement is the cost function, which need to be extended in order to quantify operation costs, reuse costs, and other economic factors affecting the operation of a system with the characteristics.

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