

Using different strategies for improving efficiency in water supply systems

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Abstract. *Nowadays, the major expenses with water supply systems (WSS) correspond to energy consumption. In WSS, the pumps are only activated when the reservoirs, responsible for supplying certain populations, reach their minimum levels. The introduction of a pump pattern adapted to energy prices variation and consumption patterns of populations can minimize energy costs significantly. In this paper, two different examples of water supply networks simulations are introduced. For these WSS the application of different optimization methods that minimize the costs associated to energy consumption in water pumping are presented. The selected optimization methods were the method of Levenberg-Marquardt (LM) and an evolutionary algorithm. In both simulated examples, the optimization of pump pattern allows significant reductions in costs associated to the pumping (up to 71%). Reductions of energy consumption are also observed in one of the examples. It was found that the optimized pump patterns take into account the variation of the energy cost throughout the day. The classic method of LM proved to be the most efficient in this kind of optimization problems. The sequential use of both methods allows further reductions with the drawback of large CPU time.*

Keywords: Cost reduction; Energy Efficiency; Optimization Algorithms; Water Supply Systems (WSS).

1 INTRODUCTION

Water and energy needs are connected. The world energy consumption for water distribution is about 7% of global energy consumption [1].

Nowadays, an increase on distance between the populations and the water sources is observed due to population growth. This means that, to supply certain populations, more energy will be needed to transport the water. At the same time, the global water consumption has quadrupled in the last 50 years and it is expected that this value continue to increase [2]. Consequently an increase on energy costs will occur. However, it is possible to optimize the way that transport and distribution of water by the populations is made, offering an important contribution to the efficiency of the WSS.

The energy required for the water pumping represents the main costs for water companies responsible for these systems [3]. It is possible to minimize energy costs associated to water pumping using a pump pattern taking into account the population consumption patterns and the variation of energy price during a day.

In this paper, we present a methodology to apply different strategies with the aim of reduce energy costs in WSS. Two different examples of water supply networks were used to test the developed methodology. The EPANET 2.0 is used to simulate and evaluate the behavior of both WSS examples in order to obtain the costs associated to energy consumption in each system. EPANET is a computer program that performs extended period simulation of hydraulic and quality behavior within pressurized pipe networks [4]. This simulator presents a robust model with a large community of users in the world [5].

1.1 Problem Formulation

An optimization problem is a mathematical model which main objective is to minimize (or maximize) something through an objective function [3].

The main goal in the presented study is to minimize the costs associated to water pumping in a WSS. The decision variables are given by a pump pattern during one day divided into 24 hours corresponding to 24 variables. Mathematically, the optimization problem can be represented by:

$$\begin{aligned} & \min_{\mathbf{x}} && \mathbf{f}(\mathbf{x}) \\ & \text{subject to} && x_i^{\min} < x_i < x_i^{\max}, \\ & && \mathbf{g}(\mathbf{x}) \geq 0, \end{aligned} \quad (1)$$

where $\mathbf{f}(\mathbf{x})$ is the objective function, i.e. the pumping energy cost for a day, $i = 1, 2, \dots, n$ represent the decision variables (in this case $n = 24$) and $\mathbf{g}(\mathbf{x})$ is a constraint function that depends on the pump operation. The value of the constraint function is zero if the simulation is well succeeded or one if some warning* appears during the simulation. To solve the errors that make appear these warnings, the exterior penalty method† is used in each iteration. In a simplified form, the objective function modified by the exterior penalty method can be expressed by:

$$f^P(\mathbf{x}) = f(\mathbf{x}) + \alpha g(\mathbf{x}), \quad (2)$$

where α is the penalty coefficient that was considered fix and equal to 500‡.

1.2 Nonlinear Optimization

In nonlinear optimization, the objective function and/or constraint functions are nonlinear [6].

The three main families of optimization algorithms are the gradient-based methods, the nature-inspired algorithms and artificial intelligence algorithms, where the two last families belong to the class of direct search methods [7].

The non-linear optimization methods based on the gradient function can find local minima through an iterative process whatever the initial guess of solution. However, frequently these are not the absolute minimum values. In major situations, the solution also depends on the initial parameters, leading to different final results [7].

The heuristic methods based on nature have the advantage of do not use the function derivatives revealing a great flexibility in modeling engineering problems but, at the same time, present as main disadvantage a large computational time [8]. These kinds of algorithms are probabilistic, so do not depend on the initial variables and use to find a global minimum most frequently.

For this study, two different methods were selected: the Levenberg-Marquardt (LM), a classic gradient-based method, and an Evolutionary Algorithm (EA), a nature-based method. Each algorithm is tested individually and in a sequential form.

The LM method is an approximation of the Gauss-Newton method [9]. If the objective function is represented by:

$$f(\mathbf{x}) = \frac{1}{2} \sum_{j=1}^m (r_j(\mathbf{x}))^2 = \frac{1}{2} \mathbf{r}(\mathbf{x})^T \mathbf{r}(\mathbf{x}), \quad (3)$$

* The main warnings that can occur are: negative pressures, impossibility in solve hydraulic equations, equilibrium conditions not satisfied or even the pump off when operating outside de range of values of its characteristic curve. Pump patterns that reproduce this kind of errors (solutions not admissible) can never be accepted in order to ensure the WSS operation.

† Exterior penalty methods can be applied in problems with equality and/or inequality restrictions [6].

‡ A high value for the penalty coefficient should be chosen in order to do not be accepted the variables that are inducing errors in the system.

where $\mathbf{r}(\mathbf{x}) = [r_1(\mathbf{x}), r_2(\mathbf{x}), \dots, r_m(\mathbf{x})]^T$ is the residual vector that consists in the individual components of the function, then for each k^{th} iteration of the optimization process, the Levenberg-Marquardt search direction, \mathbf{d}_k , is determined by solving the following linear system of equations [9]:

$$(\mathbf{J}^T \mathbf{J} + \mu_k \mathbf{I}) \mathbf{d}_k^{LM} = -\mathbf{J}^T \mathbf{r}, \tag{4}$$

where \mathbf{J} is the Jacobian matrix $m \times n$ given by the first order derivatives of the residual components r_j , μ_k is the Levenberg-Marquardt parameter and \mathbf{I} represents the identity matrix. Thus, in each k^{th} iteration, the new variables can be determined by:

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \mathbf{d}_k^{LM}. \tag{5}$$

The numerical estimation of the function gradient can be carried out using the finite differencing technique [10] which, although very sensitive to the perturbation parameter, does not need a complex numerical development [7]. This was the technique used in the proposed problem.

The EA, instead of starting with just one initial solution, starts with a population (set of solutions). During the optimization process, in each generation (iteration), the population passes through genetic processes (selection, crossover, mutation and elitism) in order to choose the most developed population containing the best individual (solution).

In the algorithm used, the population size is 20 individuals (solutions) and the maximum number of generations considered is 2000. The iterative process only stops when this maximum number of generations is reached. The description this algorithm code can be consulted in table 2.

1.3 Implementation

The process of testing the behavior of each WSS with the replacement of the corresponding pump patterns in order to obtain the minimum energy cost is very time consuming due to the large number of decision variables. For this reason we develop an interface in C++ that makes this process automatic (see Figure 1).

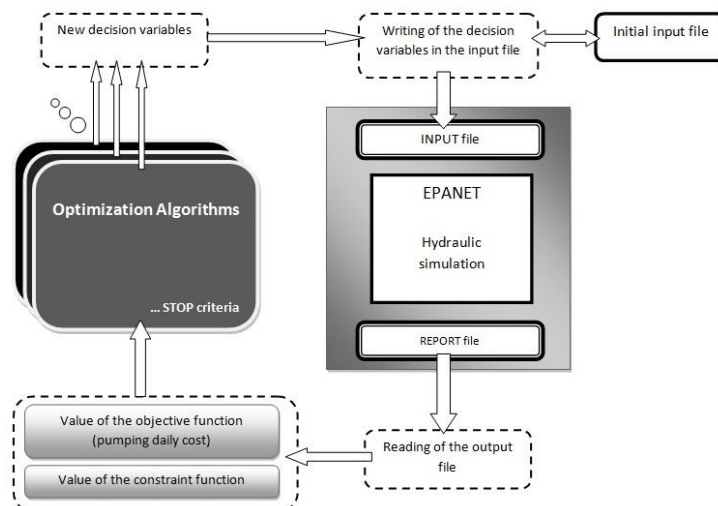


Figure 1: Description of the developed methodology.

The presented methodology starts with an initial input file containing all the characteristics of the WSS that is suppose to optimize. The input file is sent to EPANET in order to run the hydraulic simulation and a report file is then provided. The interface proceeds to the reading of some values present in the respective file as the value of

the objective function and the constraint function. These values are sent to the optimization module and new decision variables are provided by the optimization algorithm. The new variables will replace the first one in the input file and a new hydraulic simulation will run. This cycle previously described is repeated until reach the stop criteria.

2 WATER SUPPLY SYSTEMS DESCRIPTION

In this section is presented the simulation of two different kinds of water supply systems and their initial characteristics are analyzed. Each system is essentially represented by one pump with an associated pattern and water consumption points. For both examples, the energy tariff considered is represented on figure 2.

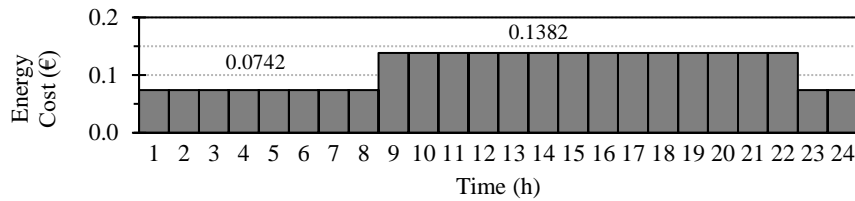


Figure 2: Daily energy tariff used in both water supply systems.

2.1 Basic WSS

This first example presented is an intuitive system due to its simplicity, which facilitates the analysis of results. The network, represented in figure 3(a), is composed of two reservoirs and one pump. Pump 1 is responsible for pumping the water from the reservoir 1 with an elevation of 50 m to the reservoir 2 with 400 m of elevation. The stored water in reservoir 2 supplies the population represented by node 3 with an elevation of 300 m and a base demand of 10 l/s. The reservoirs 1 and 2, with a diameter of 100 m and 40 m respectively, have a minimum level of 0.5 m and a maximum level of 5 m. Their initial levels are, respectively, 1 m and 2 m. The pump presents an optimum operational point for 350 m of head at a flow of 60 l/s. Its characteristic curve is represented in figure 3(b). In this figure, it is observed that the pump does not have a linear behavior with the flow variation, which is one demonstration of the non-linearity of the proposed problem.

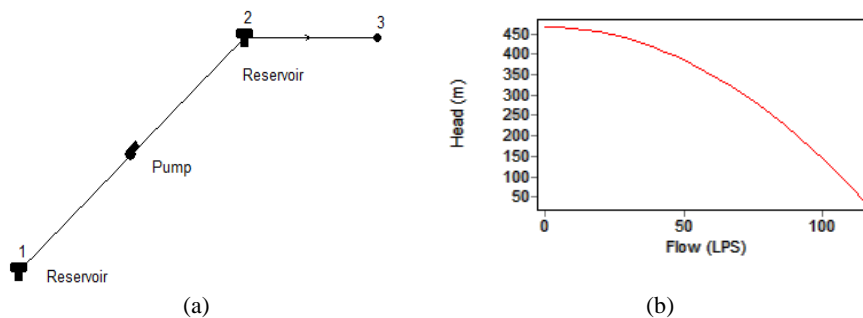


Figure 3: Representation of the basic water supply system (a) and characteristic curve of the pump (b).

The main characteristics of the presented WSS during the 24 hours of simulation are presented on figure 4. The values for the daily costs and energy consumption are also available in table 1.

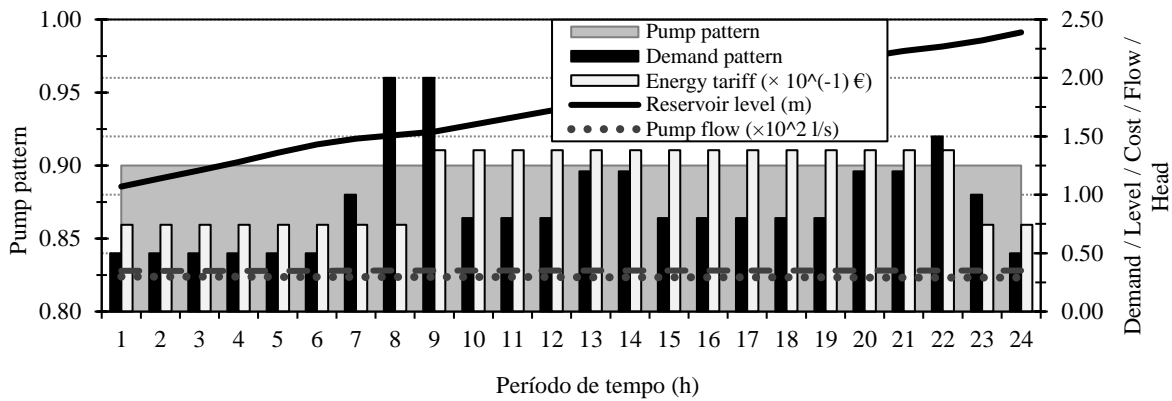


Figure 4: Initial characteristics of the basic water supply system.

With the constant pattern attributed to the pump, it is possible to see that, during all the simulation period, the flow provided by the pump (around 30 l/s) exceeds the consumption required for the population, so it is also observed a gradual increase on the reservoir level.

Analyzing the table 1, there is no significant difference between the maximum and the average power required by the pump. This is because the pump always needs the same power to overcoming the difference on elevation between the two reservoirs.

Table 1: Initial values of cost and energy consumption obtained to the pump of the basic water supply system, as the maximum and average power required.

| Energy consumption (kWh/m ³) | Average power (kW) | Maximum power (kW) | Daily cost (€) |
|--|--------------------|--------------------|----------------|
| 1,27 | 134,79 | 136,48 | 242,26 |

2.2 Two-loop WSS

In order to test the developed methodology in a more complex system, a meshed water supply network was simulated for the same period of time presented in the previous example. This network, represented in figure 5(a), presents two loops and is composed by one reservoir (water source) with an elevation of 213 m, one storage reservoir with 253 m of elevation and one pump responsible for pumping the water from the source to all points of consumption (nodes). The storage reservoir, which diameter is 9 m, presents an initial level of 1 m. Its minimum and maximum levels are, respectively, 0 and 6 m. The elevations and consumptions that characterize each node of the system as all the pipes dimensions are described in tables 4(a) and 4(b).

The pump represented on this system can deliver 57.5 m of head at a flow of 18 l/s. Its characteristic curve can be consulted in figure 5(b).

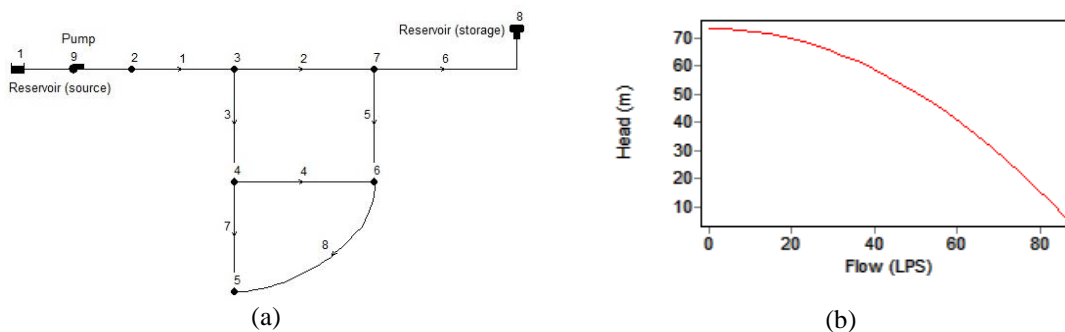


Figure 5: Representation of the two-loop water supply system (a) and characteristic curve of the pump (b).

Table 4: Properties considered for pipes (a) and nodes (b) on the two-loop water supply system. C-Factor corresponds to the coefficient of the Hazen-Williams formula to calculate head losses on the pipes.

| (a) | | | | (b) | | |
|-------|------------|---------------|----------|-------|---------------|--------------|
| Pipes | Length (m) | Diameter (mm) | C-Factor | Nodes | Elevation (m) | Demand (l/s) |
| 1 | 915 | 200 | 100 | 2 | 213 | 0.1 |
| 2 | 1525 | 100 | 100 | 3 | 216 | 1.2 |
| 3 | 1525 | 150 | 100 | 4 | 213 | 7.0 |
| 4 | 1525 | 80 | 100 | 5 | 198 | 9.1 |
| 5 | 1525 | 80 | 100 | 6 | 213 | 1.1 |
| 6 | 2134 | 80 | 100 | 7 | 213 | 1.1 |
| 7 | 1525 | 150 | 100 | | | |
| 8 | 2134 | 80 | 100 | | | |

For the hydraulic simulation with EPANET 2.0, the Hazen-Williams formula was selected with the aim of include pipe head losses on the system[§].

The initial characteristics of the two-loop WSS are represented in figure 6. In this system was chosen a different initial pump pattern, adapted to the energy price variation during a day. So is possible to see by the figure 6 that in the period between the 8 and 22 hours (higher energy price), the storage reservoir is emptying due to the reduced flow provided by the pump.

The energy consumption and cost associated to the pump of this system, as the average and maximum power needed for the pumping are presented in table 5. Observing the table, for this example, there is a difference between the values of maximum and average power required by the pump. Due to the existence of two loops on the system, at a specific period of the day (high energy price) occurs the change of the flow direction in some pipes at the same time that the storage reservoir is providing water to the network. Thus, in this situation, the power required by the pump decreases because is not necessary to provide water to all the nodes.

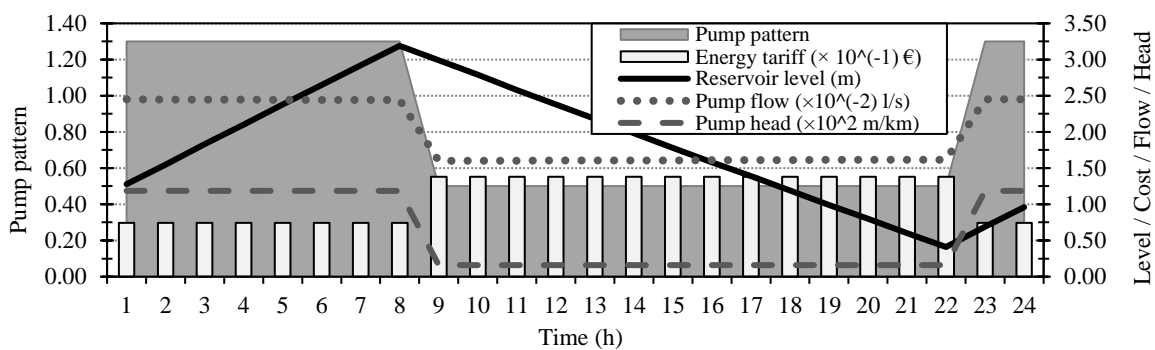


Figure 6: Initial characteristics of the two-loop water supply system.

Table 5: Initial values of cost and energy consumption obtained to the pump of the two-loop water supply system, as the maximum and average power required.

| Energy consumption (kWh/m ³) | Average power (kW) | Maximum power (kW) | Daily cost (€) |
|--|--------------------|--------------------|----------------|
| 0,21 | 17,75 | 37,96 | 34,61 |

[§] Note that these head losses contribute to increase the non-linearity of the system.

3 OPTIMIZATION RESULTS

3.1 Basic WSS

The results obtained with the optimization of the basic WSS using the Levenberg-Marquardt method (LM) and the Evolutionary Algorithm (EA) are presented in table 6.

As the EA are probabilistic, it is not usual to obtain the same final result in consecutive executions. For this reason the algorithm was executed 6 times and the average value was considered.

It is observed by the table 6 that the LM was the most efficient method, reducing the pumping costs 70% in just 88 evaluations, presenting the lowest CPU time. On the other hand, the performance of the EA was not as good as the LM. The EA took an average of 12014 evaluations of the objective function that resulted in a much more expensive CPU consuming with lower cost reductions.

There was expected, in this kind of problem, a better performance with the EA, however that was not observed. Although the objective function cannot be acceded, it may probably correspond to a smooth and convex function and so best results were obtained with the classic gradient-based method.

Table 6: Values obtained with the optimization of the basic water supply system with the Levenberg-Marquardt method (LM) and the Evolutionary Algorithm (EA).

| Method | Energy consumption (kWh/m ³) | Average power (kW) | Peak power (kW) | Cost (€/day) | Energy reduction | Cost reduction | Evaluations number | CPU time |
|-----------------|--|--------------------|-----------------|--------------|------------------|----------------|--------------------|----------|
| LM | 1,27 | 50,97 | 106,28 | 107,92 | 0% | 70% | 88 | 0,81% |
| EA1 | 1,27 | 87,41 | 195,53 | 223,91 | 0% | 38% | 11994 | 99,29% |
| EA2 | 1,27 | 104,3 | 259,94 | 264,35 | 0% | 27% | 12055 | 99,81% |
| EA3 | 1,27 | 93,67 | 203,21 | 232,75 | 0% | 35% | 11968 | 99,10% |
| EA4 | 1,27 | 97,68 | 224,05 | 257,30 | 0% | 29% | 11928 | 98,76% |
| EA5 | 1,27 | 81,37 | 172,77 | 200,47 | 0% | 44% | 12078 | 100,00% |
| EA6 | 1,27 | 96,32 | 185,72 | 256,93 | 0% | 29% | 12063 | 99,86% |
| \overline{EA} | 1,27 | 93,46 | 206,87 | 239,28 | 0% | 34% | 12014 | 99,47% |

The evolution of the objective function value for each applied method and the comparison of both are presented on figure 7.

In the case of the LM method (figure 7(a)), the existence of some peaks in the value of the objective function, corresponds to the occurrence of errors during the simulation. As the variables responsible for these values could not be accepted, the corresponding iterations were removed. So the improved function evolution was also represented.

For the first 25 iterations there are no variations in the function value because in this method those iterations are needed for the derivative calculations. After these iterations is observed a faster convergence of the function to the minimum value.

In respect to the function evolution for the EA (figure 7(b)) the convergence is not so fast. Moreover, each execution presents different convergences. This corresponds to expected results for this kind of method.

The figure 7(c) shows the clear difference between convergences of both selected methods in this system.

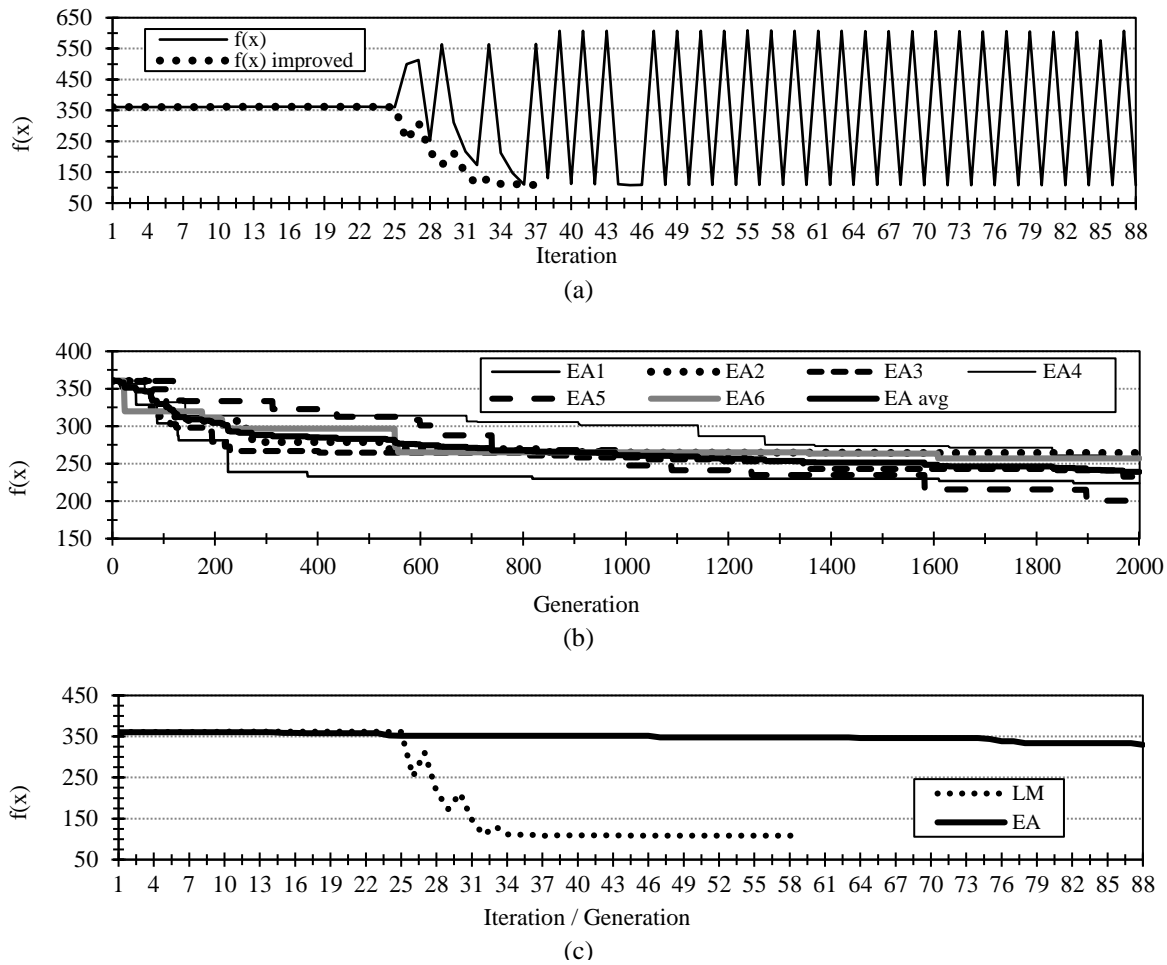


Figure 7: Evolution of the objective function value during the optimization process of the basic water supply system with the Levenberg-Marquardt method (a), the Evolutionary Algorithm (b) and the comparison between both (c).

In order to analyze how the optimized system works, it is presented, in figure 8, the main characteristics of the system optimized with the different methods.

Comparing the optimized pump pattern presented in figure 8(a) with the evolution of the decision variables in LM method (figure 9), it is observed an existence of two paths that are followed by the variables values according to the energy tariff (high cost and low cost periods). Although the lowest pump flow during the 23 to 7 hours period, this still exceeds the required by the populations, so the reservoir is filling during this period of time. On the other hand, during the high cost period (8-22h), the pump flow is not enough to supply the population and the reservoir is emptying.

Analyzing the optimization with the EA, in figure 8(b) it is observed almost a random distribution of the variables which constitute the pump pattern. As in these methods the probability of best-fit variables being chosen is higher, it is expected, with the increase of the number of generations, a tendency of the pump pattern to the same obtained with the LM. However the resulting CPU time could not be viable when compared with the LM case.

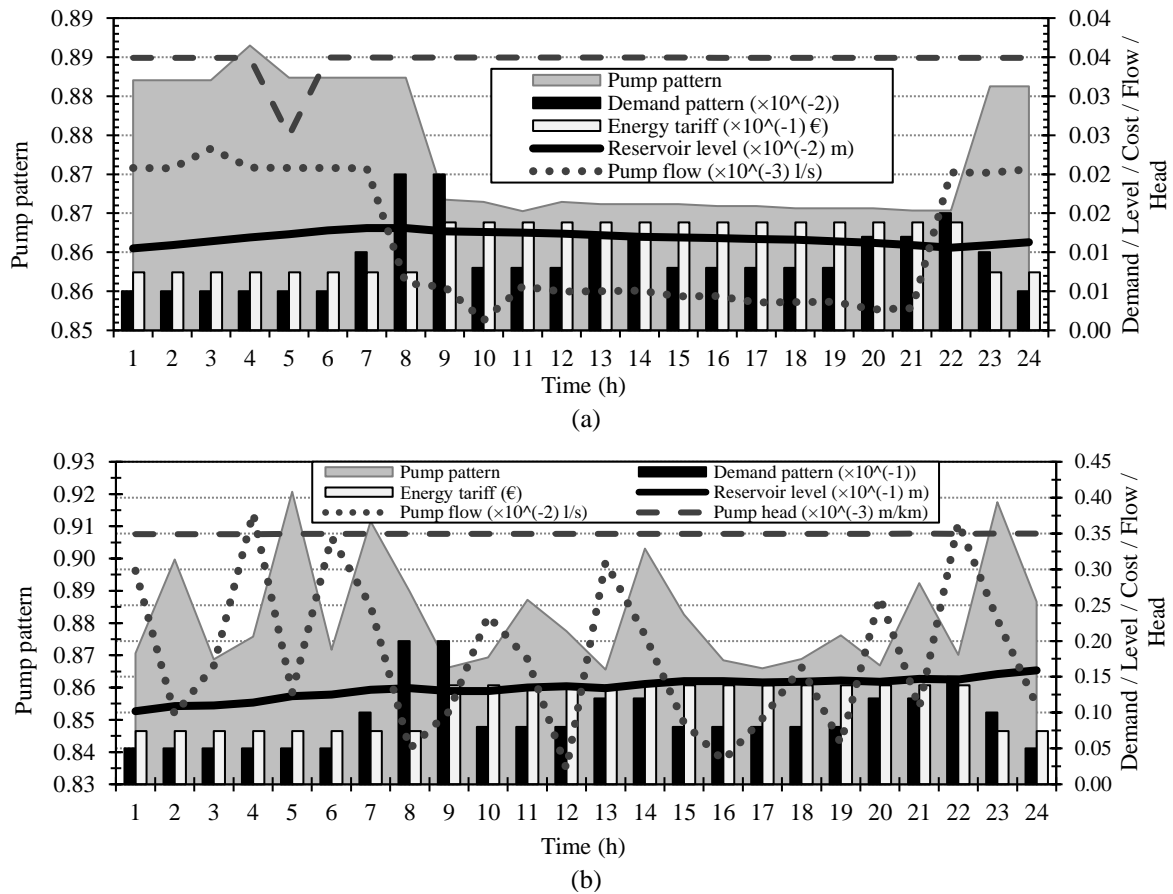


Figure 8: Characteristics of the optimized basic water supply system with the Levenberg-Marquardt method (a) and with the Evolutionary Algorithm (the best values obtained, EA5, were selected) (b).

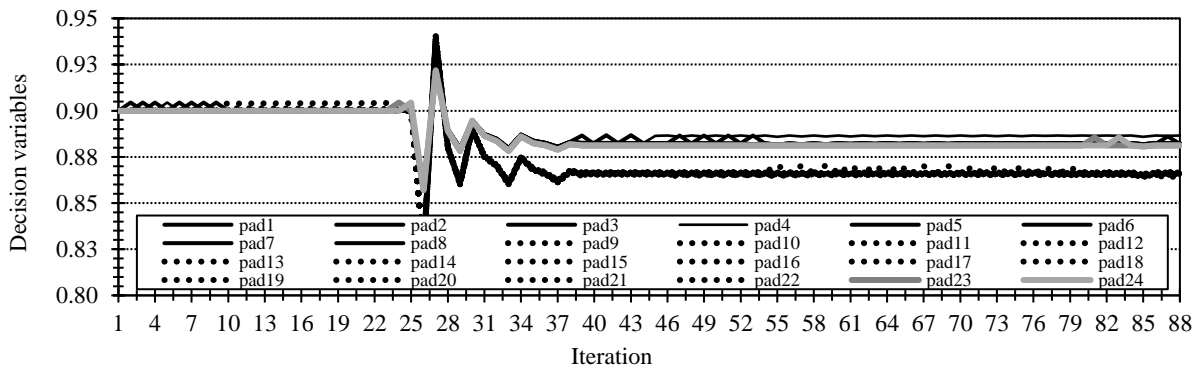


Figure 9: Evolution of the decision variables obtained during the optimization with Levenberg-Marquardt method in the basic water supply system.

3.1.1 Optimization strategies

With the aim of testing the different algorithms sequentially, a cascade optimization strategy was applied. This strategy consists in start the iterative process with the LM method using the obtained variables to start a new optimization process with the EA (LM+EA). The same was repeated but ending the optimization process with the LM (LM+EA+LM). As in each execution of the EA different results are obtained, there was considered the

average of 6 executions of each strategy applied.

No significant improvements were observed in this system optimization. The results still presenting no energy reductions and the cost reductions were also about 70 % as in the initial LM method applied.

3.2 Two-loop WSS

The results for the optimization of the two-loop water supply system are presented in table 7. For this example there was observed that the average of the values obtained for the EA (10% of reduction in energy and 11% of reduction in costs) is very similar to the values obtained with the LM (10% of reduction in energy and 14% of reduction in costs), however the LM method presents less time consume. Observing the first two executions of the EA (EA1 and EA2), it is seen that better reductions of energy and associated costs are achieved.

In this case, both algorithms present a good performance; however the results with the EA probably could be improved if the number of executions were increased.

With the aim of understand better how each algorithm works during the optimization process, it is presented, in figure 10, the evolution of the values of the objective function.

For the two-loop system, the behavior of the optimization algorithms during the simulation is similar to the basic system. In this example, it is also observed the existence of some peaks in the LM function evolution, corresponding to variables not acceptable in the problem. Solving this, it is observed a faster convergence of the LM method when compared with the EA.

Table 7: Values obtained with the optimization of the two-loop water supply system with the Levenberg-Marquardt method (LM) and the Evolutionary Algorithm (EA).

| Method | Energy consumption (kWh/m ³) | Average power (kW) | Peak power (kW) | Cost (€/day) | Energy reduction | Cost reduction | Evaluations number | CPU time |
|-----------------|--|--------------------|-----------------|--------------|------------------|----------------|--------------------|----------|
| LM | 0,19 | 15,1 | 31,81 | 29,78 | 10% | 14% | 88 | 0,89% |
| EA1 | 0,15 | 11,36 | 33,63 | 24,93 | 29% | 28% | 11780 | 98,68% |
| EA2 | 0,16 | 11,72 | 41,8 | 25,52 | 24% | 26% | 11740 | 98,34% |
| EA3 | 0,2 | 16,61 | 39,05 | 32,77 | 5% | 5% | 11938 | 100,00% |
| EA4 | 0,21 | 17,61 | 38,37 | 34,36 | 0% | 1% | 11673 | 97,78% |
| EA5 | 0,21 | 17,23 | 39,4 | 33,74 | 0% | 3% | 11741 | 98,35% |
| EA6 | 0,2 | 16,75 | 37,07 | 32,97 | 5% | 5% | 11741 | 98,35% |
| \overline{EA} | 0,19 | 15,21 | 38,22 | 30,72 | 10% | 11% | 11769 | 98,58% |

In figure 11 is presented the main characteristics of the two-loop system optimized by the LM method and by the EA. In this system, similar characteristics with the basic optimized system are also observed.

With the LM method, the variables are exactly according to the energy price variation during the simulation period (see figures 11(a) and 12).

In the optimization case with EA, for this WSS, the final variables are not as random as in the previous example. It is possible to see the pumping operating according to the variation of the energy price.

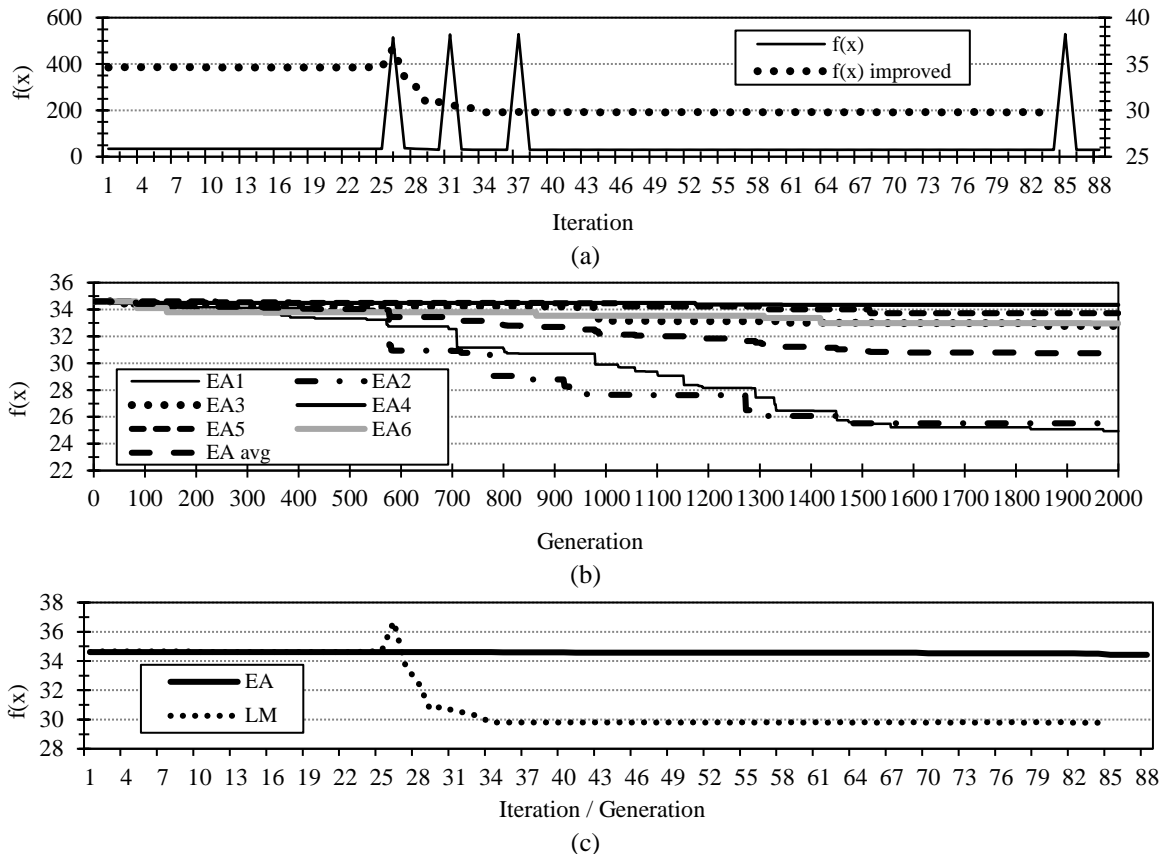


Figure 10: Evolution of the objective function value during the optimization of the two-loop water supply system with the Levenberg-Marquardt method (a), the Evolutionary Algorithm (b) and the comparison between both (c).

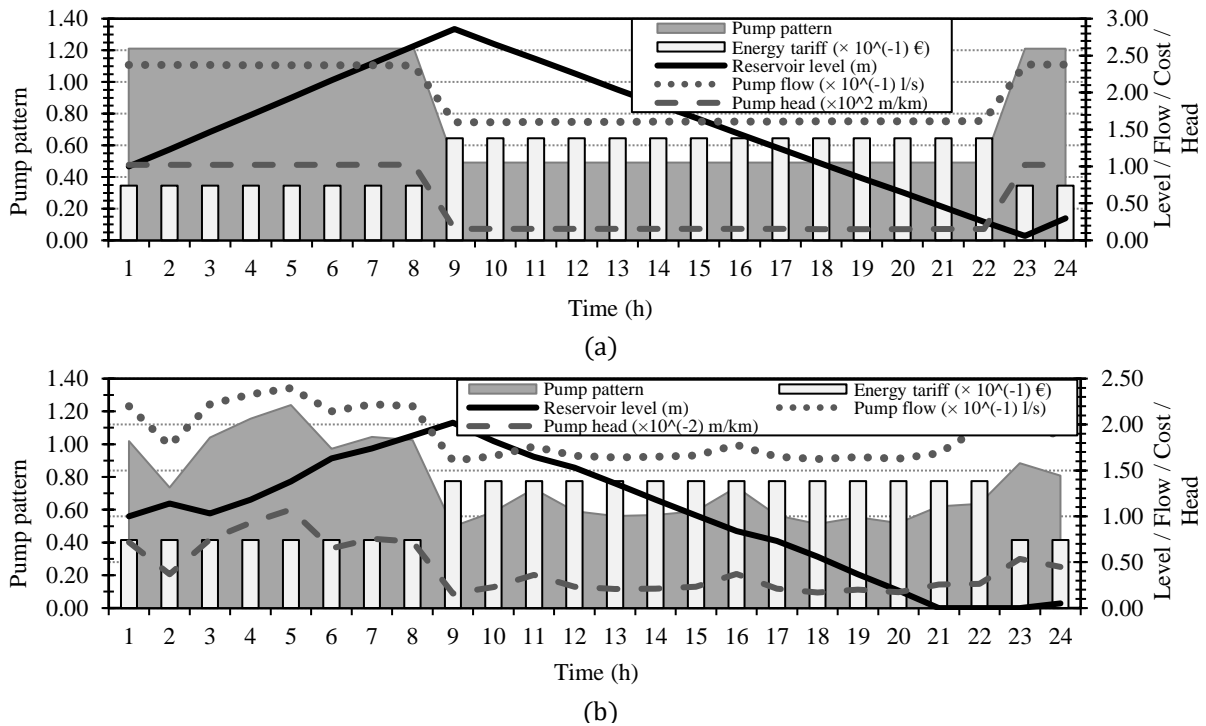


Figure 11: Characteristics of the two-loop water supply system after optimization with the Levenberg-Marquardt method (a) and with the Evolutionary Algorithm (the best values obtained, EA1, were selected) (b).

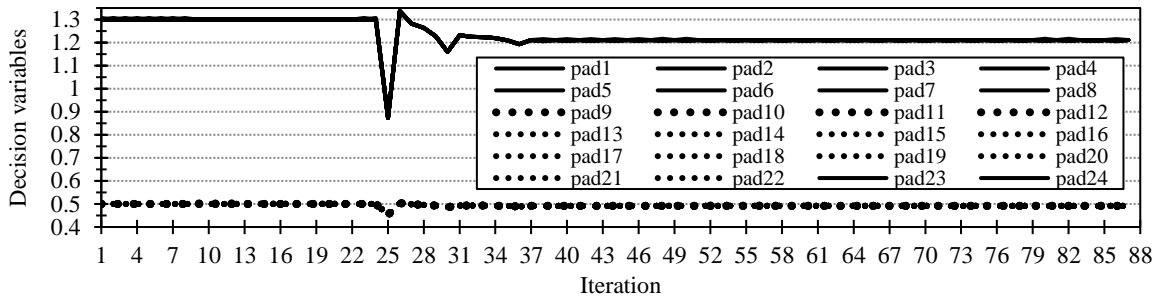


Figure 12: Evolution of the decision variables obtained during the optimization with Levenberg-Marquardt method in the two-loop water supply system.

3.2.1 Optimization strategies

The same optimization cascade strategy was tested in this system hoping for better results. However, as was occurred in the previous example, no significant improvements were found when compared with the LM method.

3.3 Results Comparison

The results obtained in both WSS tested can be compared by the analysis of the table 8.

LM method, in both WSS examples, presents the best performance with higher reductions in a significant reduced number of iterations.

About EA in the two-loop system, although the average values obtained, in some executions of the algorithm there were observed great values of energy and costs reduction (29 % and 28 % respectively).

Globally, the reductions in energy costs were better in the basic systems. As the two-loop WSS is more complex and includes head losses, the optimization problem becomes more difficult to solve due to the higher level of nonlinearity.

Table 8: Comparison of the optimization results obtained in both examples of water supply systems.

| WSS | Method | Energy reduction | Cost reduction | Evaluations number |
|----------|-----------------|------------------|----------------|--------------------|
| Basic | LM | 0% | 70% | 88 |
| | \overline{EA} | 0% | 34% | 12014 |
| | EA_{max} | 0% | 44% | 12078 |
| Two-loop | LM | 10% | 14% | 88 |
| | \overline{EA} | 10% | 11% | 11769 |
| | EA_{max} | 29% | 28% | 11780 |

3.4 Sensibility Analyses

The sensibility analyses are important to understand which parameters during all the optimization processes have significant influence on the final results. So it is presented, in the next subsections, two kinds of analyses that were considered relevant.

3.4.1 Sensibility to the initial decision variables

As the LM is a gradient-based method, a dependence of this algorithm with the initial decision variables is

expected. On the other hand, as the EA is an exploratory method, it is not expected the same. For this reason, the behavior of both optimization methods with a different initial solution was analyzed.

In the basic system (section 3.1), starting with a constant pump pattern, the results were better than the two-loop system (section 3.2) so, in the present section, the two-loop system with a constant initial pump pattern (of multiplier 0,9) is analyzed too. The results can be consulted in table 9.

Table 9: Values obtained with the optimization of the two-loop water supply system starting with a constant initial pump pattern (0,9).

| Method | Energy consumption (kWh/m ³) | Average power (kW) | Peak power (kW) | Cost (€/day) | Energy reduction | Cost reduction | Evaluations number | CPU time |
|-----------------|--|--------------------|-----------------|--------------|------------------|----------------|--------------------|----------|
| Initial values | 0,20 | 14,88 | 14,93 | 39,83 | - | - | - | - |
| LM | 0,1 | 6,4 | 9,66 | 15,37 | 50% | 61% | 144 | 0,56% |
| EA1 | 0,12 | 8,41 | 18,6 | 20,73 | 40% | 48% | 11828 | 99,06% |
| EA2 | 0,12 | 8,36 | 20,1 | 20,77 | 40% | 48% | 11940 | 100,00% |
| EA3 | 0,13 | 9,08 | 27,51 | 21,42 | 35% | 46% | 11887 | 99,56% |
| EA4 | 0,11 | 7,22 | 17,53 | 18,62 | 45% | 53% | 11845 | 99,20% |
| EA5 | 0,13 | 8,85 | 20,48 | 22,66 | 35% | 43% | 11811 | 98,92% |
| EA6 | 0,12 | 8,51 | 29,78 | 21,04 | 40% | 47% | 11881 | 99,51% |
| \overline{EA} | 0,12 | 8,41 | 22,33 | 20,87 | 39% | 48% | 11865 | 99,37% |

Starting with a constant pattern of multiplier factor 0.9, the daily energetic cost associated to the pumping is 39,83 €.

Comparing the values of table 9 with the values of table 7, a significant improvement on energy and costs reduction is observed. As was expected, LM method demonstrated its dependence with initial variables, giving the lowest value presented in this study for the daily energy cost in two-loop WSS (15,37€).

3.4.2 Sensibility to the LM parameters

In the table 10 there are presented the results of the sensibility of both WSS to the perturbation parameter of the finite differencing technique used in the LM method for the derivatives calculation.

Table 10: Optimization results with different perturbation parameters of the finite difference used in the LM method.

| WSS | Parameter of perturbation | Energy reduction | Cost reduction | Evaluations number | CPU time |
|----------|---------------------------|------------------|----------------|--------------------|----------|
| Basic | 0,001 | 0% | 74% | 93 | 0,28 |
| | 0,005 | 0% | 70% | 88 | 0,28 |
| | 0,010 | 0% | 63% | 85 | 0,27 |
| | 0,015 | 0% | 59% | 84 | 0,25 |
| Two-loop | 0,001 | 5% | 5% | 150 | 0,77 |
| | 0,005 | 10% | 14% | 88 | 0,45 |
| | 0,010 | 10% | 12% | 133 | 0,67 |
| | 0,015 | 14% | 16% | 132 | 0,67 |

The selected parameter, used in all the results previously presented, was the 0,005 because it was considered the most reasonable value. However, as it is seen by table 10, there is a possibility of obtaining higher cost reductions

in the basic system using the parameter 0,001 or even of obtaining higher energy and costs reductions in the two-loop system using a perturbation of 0,015.

4 DISCUSSION AND CONCLUSIONS

Globally, the optimization methods applied in both examples of WSS reveal a great behavior, reducing the costs from 14 % (two-loop system) to 70 % (basic system) with the LM method and from 11 % (two-loop system) to 34 % (basic system) with the EA. However, LM method presented better efficiency due to the lowest computational consuming. On the other hand, the use of both methods sequentially did not demonstrate significant improvements when compared with the first results obtained with the LM.

The developed methodology can have an important application in real water supply systems for their efficiency improvement. However, some details, as constraints in initial and final level reservoirs, must be refined. The energy consumption should also be considered in the optimization process and not only energy costs, leading us to a multi-objective optimization problem.

In future works is pretended the association of the presented methodology with energy production (recovering the wasted energy in WSS) and with others optimization methods in order to reach the maximum efficiency of the WSS.

ACKNOWLEDGEMENT

Coelho, B. thanks the *Fundação para a Ciência e a Tecnologia* (FCT) Portugal for the Ph.D. grant SFRH/BD/82191/2011.

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