LIFE SWSS

"Smart Water Supply System"

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List of Abbreviations

AdA	Águas do Algarve
EPAL	Empresa Portuguesa das Águas Livres, SA
GA	Genetic Algorithm
GHG	Greenhouse gas
SWSS	smart water supply systems
WSS	water supply systems

1 – Introduction

1.1. Project Background

Water supply systems (WSS) are large-scale systems that treat and transport water over vast geographical areas to consumers, being crucial a safe and efficient operation of these systems. These systems lead to significant environmental impacts due to huge amount of energy consumed in water pumping, associated GHG emissions, and water leakages. Current control systems are designed to deliver water accordingly to specific demands, but frequently not efficiently. Besides that, water networks operation and management still relies on the utilities accumulated experience, which arises a question "if the water supply systems are most of the times inefficient, why aren't utilities already implementing advanced approaches such as the ones being proposed in LIFE SWSS?"

The project aims to demonstrate an innovative platform (SWSS) for management and decision support for water supply systems (WSS) under real working conditions. The SWSS platform will be composed by five modules:(1) Predictive, (2) Hydraulic simulation, (3) Assessment, (4) Leakage and (5) Optimization, which together will support the water companies to improve energy efficiency and water efficiency in their systems. The SWSS modules are based on previous developments from consortium partners, which will be integrated in one single platform in this project. The SWSS platform will be demonstrated in 3 demonstration WSS from AdA, EPAL-Centre and EPAL-West, which were selected due to their distinctive characteristics and instrumentation level.

1.2 Goal and Scope Definition

This document is a report containing the developments and produced results of module (5) Optimization.

The objective of this module is to optimize the water pumping schedule of a specific WSS, i.e find the optimal switching on/off sequence of for each pump throughout 24h, aiming to minimize the cost of the pumping operation. All the physical constraints of the water system, and water demands, must be complied.

The WSS structure, the daily demands, and the system constraints limit the optimal solutions search. Consequently, in order to achieve further enhanced results, the algorithmic implementation of the optimization module is adaptive to the studied WSS.

The detailed methodology is presented in Chapter 2, which presents the problem definition, and the modelling and the optimization approaches. Chapter 3 presents the results for a specific case study. And, finally in Chapter 4, the conclusions are highlighted.

2 – Methodology

2.1. Problem definition

A water distribution network is mainly composed by reservoirs, nodes, and water pumps (Fig. 1). The pump scheduling problem is defined by the process of selecting which of the available pumps in the system should be used to supply water to a specific node or reservoir, and when it should perform such operation (i.e. which periods of the day should the pumps be activated).

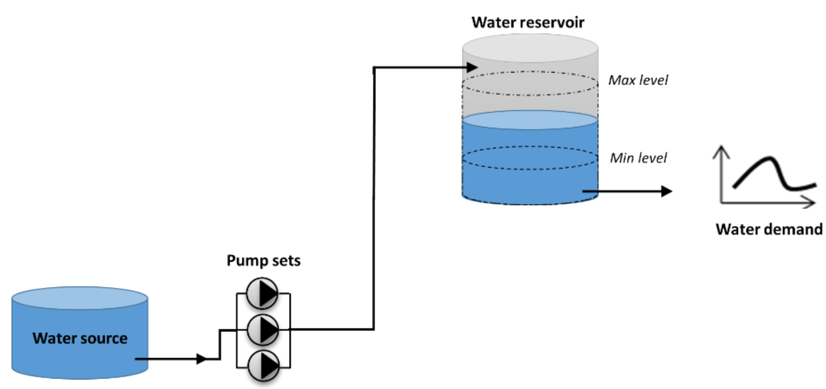

Figure 1. Simplified example of a distribution system with one water source, three pumps, and one water reservoir with specific water levels.

The objective of pump scheduling is to minimize the cost of the pump operation in water supply systems.

Naturally, the water supply system must be working properly, i.e. the pump scheduling should be not only feasible but also compatible with the physical and operational constraints of the system. Important water system constraints are as such:

i) maintaining sufficient water within the system's reservoirs, or within specific levels, to meet the time dependent water demands,

ii) water distribution network physical compliance, or

iii) technological constraints of pumps.

Depending on the size of the water system, number of pumps, nodes, and reservoirs, to modelling such system may be very extensive analytically. Although, there are several software that model water distribution and piping systems, the optimization problem become complex, and algorithms which depend on the full analytical formulation of the problem become useless.

Moreover, important factors influencing the cost are the electricity tariff structure, the efficiencies of the pump sets concerning the pumping needs, maintenance costs.

2.2. Water system modelling

Modelling water distribution systems aims to create a virtual idealization of the real network, by properly simulating and analysing the network piping, nodes, reservoirs, pumps, terrain topology. As referred before connecting all these components and comprising with the water demand and physical restrictions of the system can become extremely complex. The goal is that hydraulic simulations reproduce the best possible approximation of the real behaviour of the studied system.

In order to model the water system, the hydraulic simulator EPANET 2.0 is used for its versatility, as it is a public domain program and widely tested by the scientific community. Figure 2 schematizes an example of a WSS network implemented in EPANET 2.0, which is inserted throughout a file with the extension .INP.

The main inputs required in EPANET 2.0 are:

- network structure (pumps, pipes, nodes, junctions, and tanks characteristics, as also terrain topography)
- hydraulic constraints
- electricity tariff
- water demands and tanks initial conditions
- operation rules

The main outputs used from EPANET 2.0 are:

- water flows
- tank levels
- hydraulic constraints accomplishment

- electricity consumption in pumping operation

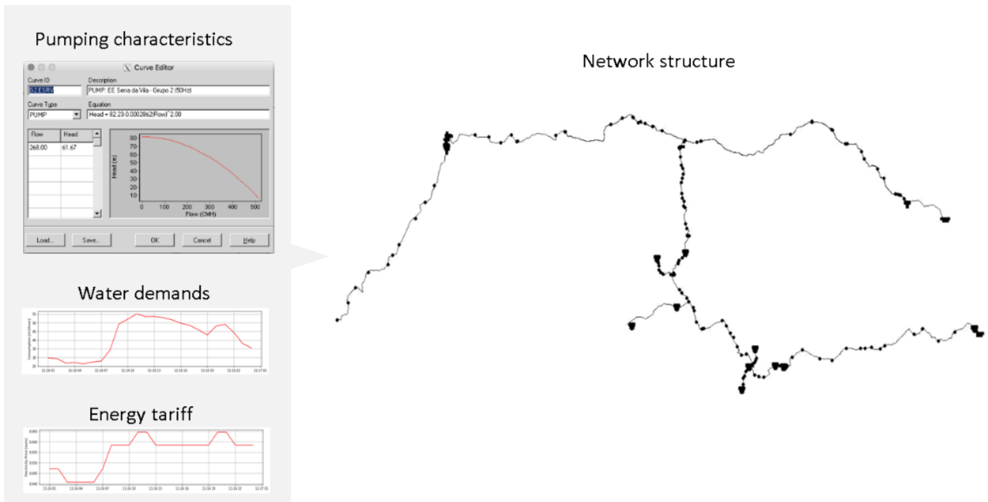

Fig. 2. Example of a hydraulic simulation of a WSS network of the using EPANET 2.0.

2.3. Optimization method

There are several types of optimisation methods which have been used to find optimal pump schedules. The network modelling is analytically complex, and the optimization search space is neither mathematically convex, differentiable, or continuous. Then, metaheuristic methods become useful, which are capable to find good approximate solutions to the real optimum in a reasonable amount of time – very useful in large search spaces. Moreover, the pump scheduling can be approached as a parametric problem (switching on/off per pump per hour, as detailed ahead).

The genetic algorithm (GA) has been widely used in the scientific research community, and has proven to be well suited to these kind of problems. The GA works using a chromosome structure (well-known terminology within genetic algorithms topic) as detailed in the following paragraphs. The chromosome is composed by the decision variables which are the pump switches (a single decision variable is known as a gene). Each possible or candidate solution defined by a set of genes is an individual, and the set of individuals assessed by the GA is known as the population.

The following details refer to the GA application.

- **Objective** - Minimize the cost of operating pumps (*F*) supplying demanded water throughout a 24h day, as defined in equation set (1) to (5).

$$minimize: \quad F = \sum_{h=1}^{h=24} T(h,d,s).P\left(h,e_i,w_p\right) \tag{1}$$

$$subject\ to, \forall\ h \in [0,24[: \quad w_p(h) \ \geq\ w_p{}^d(h) \tag{2}$$

$$w_n(h) \ \geq\ w_n{}^d(h) \tag{3}$$

$$w_r(h) \geq\ w_r{}^d(h) \tag{4}$$

$$w_r{}^{l,min} \ \leq w^l{}_r(h) \leq\ w_r{}^{l,max} \tag{5}$$

where the used parameters are as follows:

T – electricity tariff (Eur/kWh)

h – time, in hours, throughout a 24h day

d – day of the week (weekday, weekend, holyday)

s – season (Winter, Spring, Summer, Autumn)

P – pumping electrical energy consumed

e_i – energy consumption in water pumping per each used pump, *i*, (kWh/m^3). This depends on the water flow in the pump and on the pump head and speed (calculated in EPANET)

w – water flow in the pump (*p*), node or junction (*n*), and reservoir (*r*) (m^3/h)

w^d – water flow demand to the pump (*p*), node or junction (*n*), and reservoir (*r*) (m^3/h)

w_r^l – water level in the reservoir (*r*). It must be between specified limits (*min, max*)

- **Constraints -** The water level in the reservoirs (w_r^l) must be between specified minimum and maximum limits ($w_r^{l,\ min}$, $w_r^{l,\ max}$). All the hydraulic and physical restrictions of the WSS network must be complied. These are determined by the WSS simulator EPANET. The constraints are evaluated for each solution, i.e. a penalty factor is attributed to the cost value of a solution if that particularly solution fails to comply with these constraints (equation (6)).

$$penalty\ factor: \quad F = \begin{cases} F + 10\,000\ ,\ if\ \forall\, h \in [0, 24[,\ \ w_r{}^{l,min}\ \geq w^l{}_r(h) \\ F + 10\,000\ ,\ if\ \ \forall\, h \in [0, 24[,\ \ w_r{}^{l,max}\ \leq w^l{}_r(h) \end{cases} \qquad (6)$$

- **System state -** The feasibility of the system evaluated by the simulation model of the water network. Each candidate solution is evaluated concerning the water system compliance. Information regarding the constraints or any physical restriction violation which could lead to the water system failure or defect function is very important and are included in the state information provided by the simulation module.

- **Decision variables (Genes) -** Switch (on/off) of each pump, per hour, during a day of 24h. Although in equation (5) there are several variables, the main decision variables are the pump switches per hour (h). The rest are dependent variables from which the majority are determined by the WSS simulator EPANET. The chromosome structure concerning the decision variables is described more ahead.

- **(Candidate) Solution -** A combination of values composing the decision variables define the pumps operation during a day of 24h is a possible solution.

Two chromosome structures may be selected, although structure (ii) is the standard in the proposed method.

i. If the number of demand points is higher than the number of pumps, then the chromosome assumes the shape as in Table 1. This configuration is less complex, and the number of pumps is the most important parameter, where the decision variables are defined as 0 or 1 (switch on or off) per hour (h), per pump. Calculating the hourly pump scheduling, for 24h (h), this simple approach produces $2^{i \times 24}$ possible combinations.

Table 1. Example of the chromosome structure used in GA (decision variables), for a number of *i* pumps throughout 24h of operation.

Pump (P_i - *i* is a specific pump)	P_1			…	P_i		
Hour (h_i - is a specific hour, h∈[1-24], where *i* is a specific pump)	$h_1 = 1$	…	$h_1 = 24$	…	$h_i = 1$	…	$h_i = 24$
Gene values (binary 0/1)	0/1	…	0/1	…	0/1	…	0/1
Meaning, i.e. number of pumps on/off	on/off	…	on/off	…	on/off	…	on/off

Example (5 pumps, 2 tanks), $2^{120\ variables} = 1.3 \times 10^{36}$ *combinations:*

Pump 1

h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
gene	1	1	0	1	0	0	0	0	1	0	1	1	0	1	1	0	1	0	0	0	1	1	0	1

Pump ...

h		...	
gene		...	

Pump 5

h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
gene	0	0	0	0	1	0	1	1	0	1	0	1	1	1	1	0	1	1	1	0	1	1	0	0

i. If the number of pumps is higher than the number of demand points, then it may become more advantageous using a chromosome such as presented in Table 2. This configuration is more complex than the previous one, since the pumps associated to each demand point must be known; however, the number of possible solution combinations is lower which may lead to a faster convergence. The decision variables are integer values defined between [0, max. number of pumps], where 0 means all pumps are switched off, and other value means the number of pumps switched on. Each water tank has its respective maximum number of pumps associated (e.g. Fig. 1 represents a tank with 3 pumps associated). Then, there is a set of decision variables per tank.

Calculating the hourly pump scheduling, for 24h (h), this approach produces n_j^{24} possible combinations per demand point DP_j.

Table 2. Example of the chromosome structure used in GA (decision variables), for a number of j demand points in the network and associated pump sets throughout 24h of operation.

Demand point (DP$_j$ - *j* is a specific demand point)	**DP$_1$**			**…**	**DP$_j$**		
Hour (h_i - is a specific hour, h∊[1-24], where *j* is a specific demand point)	h_1 =1	…	h_1 =24	…	h_j =1	…	h_j =24
Gene values (integer value, n, ranged by specific limits for each DP$_j$ – from 0 to n_j)	n_1	…	n_1	…	n_j	…	n_j
Meaning, i.e. number of pumps on/off (0, 1, 2…max num. pumps n_i)	Pumps on/off	…	Pumps on/off	…	Pumps on/off	…	Pumps on/off

Example (5 pumps, 2 tanks, where in tank 1 there are 3 pumps, and in tank 2 there are 2 pumps), $4^{24\ variables} + 3^{24\ variables} = 2.8 \times 10^{14}$ *combinations*

Tank1 (3 pumps associated)

h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
gene	1	2	0	0	0	1	2	2	3	2	1	1	0	0	1	3	1	3	0	0	1	1	0	1

Tank 2 (2 pumps associated)

h	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
gene	0	0	0	2	1	0	1	1	0	1	0	2	1	1	1	0	1	2	2	0	1	1	0	0

The optimization module (coded in PYTHON), and its coupling with the simulation module composed by EPANET 2.0 to perform the solutions evaluation is exemplified in Fig. 3.

First an initial population is generated with N individuals, which are afterwards evaluated. The initial population is generated randomly, or by selecting individuals know to produce feasible results (this should be made carefully because it may accelerate the convergence but increases local optima issues). Individuals that do not comply with constraints are penalized. Then, a selection procedure selects a percentage of the best solutions to generate the offspring population (O_i) using crossover and mutation operators. Subsequently, the offspring population is evaluated and a selective mutation procedure is followed for individuals having high penalty factors – this increases convergence.

In this knowledge-based selective mutation, individuals with pumping schedules that lead to excess of water in reservoirs, have some of their pumps switched off, and individuals with leading to lack of water in reservoirs, have some of their pumps switched on. And then, these individuals are returned beck to the offspring population.

The best individuals from the offspring population are reinserted to the main population and the loop continues till a maximum number of generations is reached.

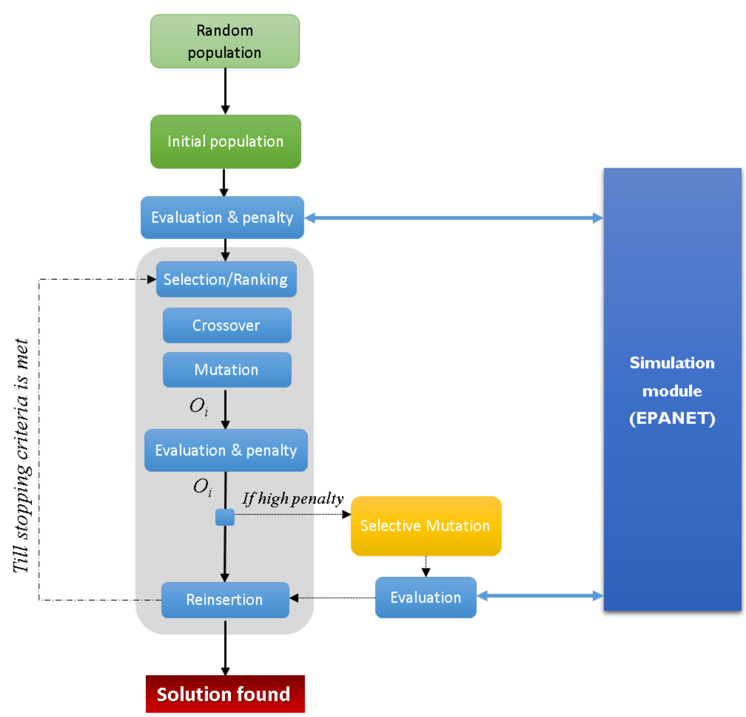

Fig. 3. Example of the algorithm structure ()

3 – Optimization preliminary results

One of the most successful approaches for optimizing the pumping schedule was to select an independent section of the whole water network. The water demand associated to this section should not be dependent on the state of adjacent sections of the network. In this way, the optimization runs are less computational expensive (although more numerous for the whole network). In this chapter we present a resume of some case studies.

One case study was composed by 2 pumps and 1 water tank. The objective is to minimize the pumping operation electricity costs considering the electricity tariff employed. The problem constraints are the water demand/consumption fulfilment, and maintain tank levels between minimum and maximum limits. The results are presented in Figures 4 and 5.

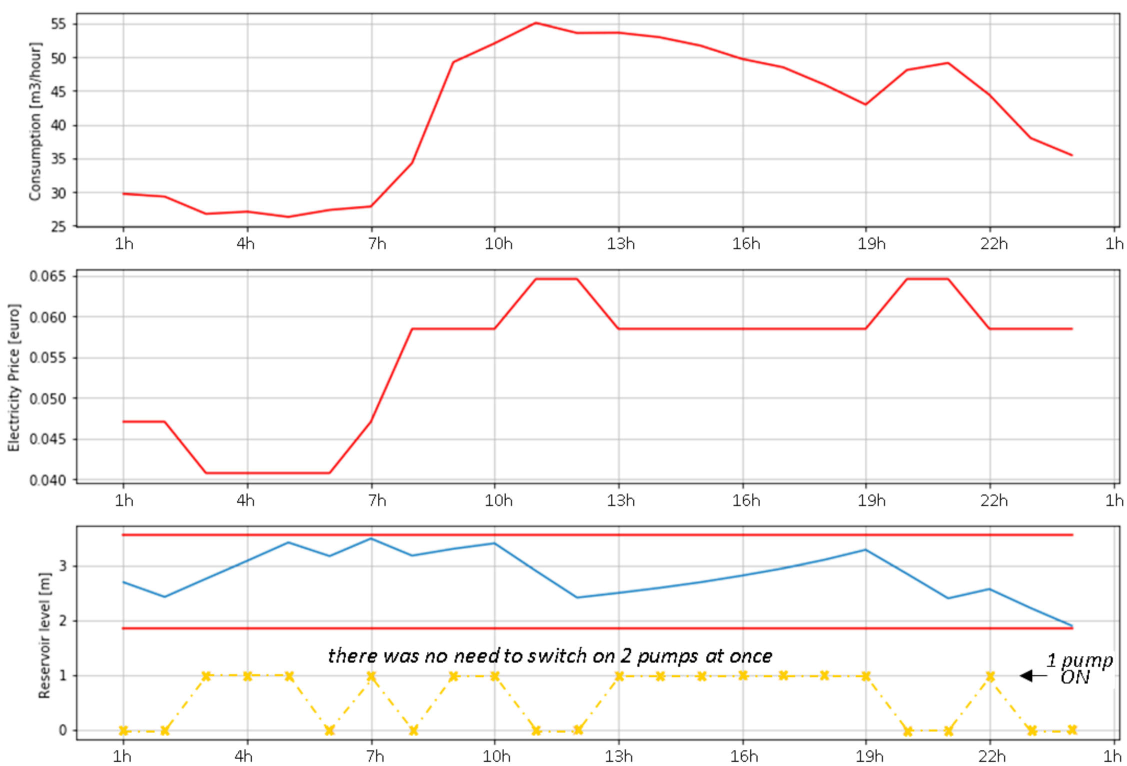

Fig. 4. Water demand in the reservoir, electricity tariff (middle), and pump switching (crosses) and reservoir levels (min/max red, instant level blue) (below), along a 24h day.

The reservoir levels were maintained at safe values (Figure 3), where the pumps were switched on or off for each 1h time step (along 24h). For this case study there was no need to switch on 2 pumps at once. Cost savings of around 10% were achieved, per 24h.

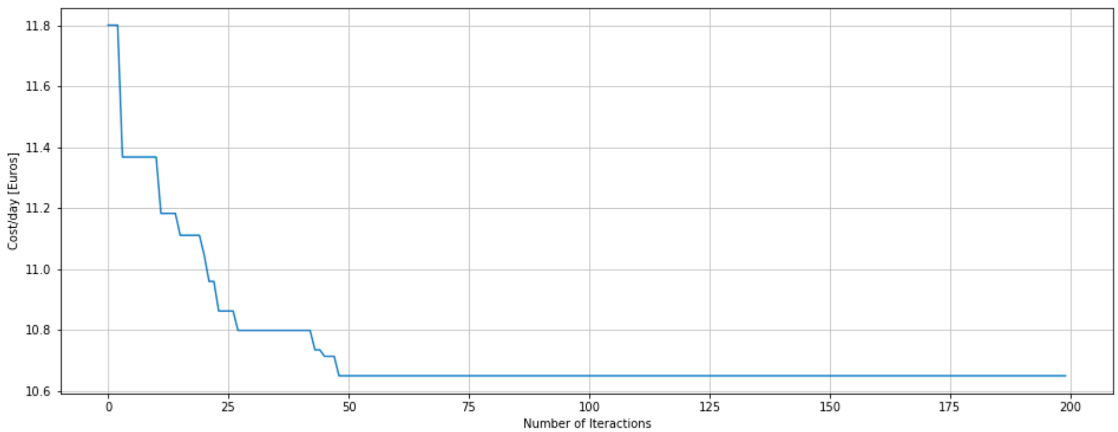

Fig. 5. Evolution of the pumping cost per day throughout the number of the algorithm interactions (generations).

A typical convergence profile for metaheuristic methods can be seen in Figure 4. For each optimized water network section tuning the GA is crucial (e.g. crossover, mutation, and elitism rates, initial population). More complex water networks will not necessarily lead to a more complex GA implementation, since the algorithmic structure will remain similar. The complexity may increase variables relationship, i.e. reducing the variables search space and increasing the convergence, but, it can increase the computation effort.

Other case study was composed by 5 pumps and 2 water tanks. Tank A has 4 pumps associated, and tank B has 2. The objective and the constraints remain the same as in previous case study, as well as the cost savings. Results are presented in Figures 6 to 8.

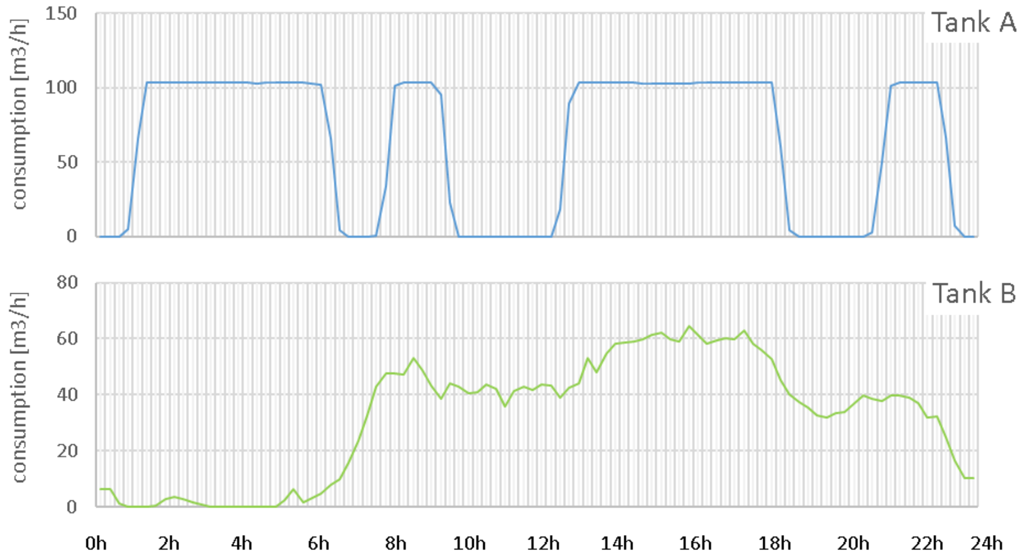

Fig. 6. Water demand in the reservoirs.

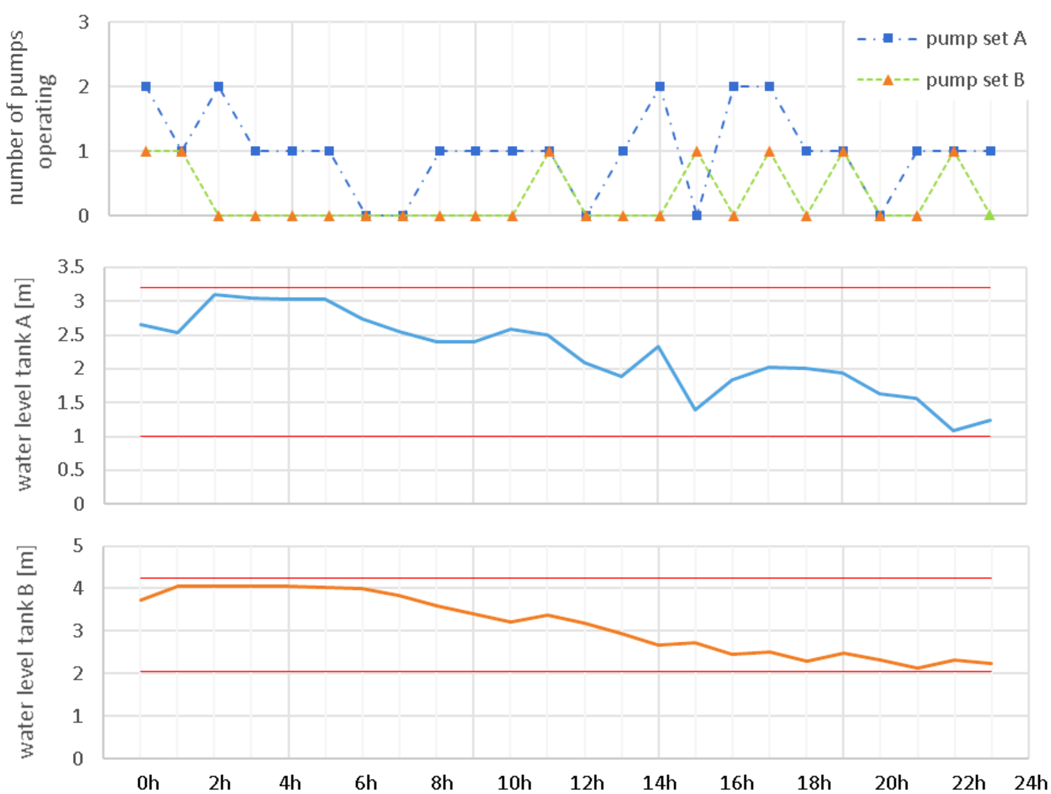

Fig. 7. Pump switching, and reservoir levels (min/max red, instant level blue and green for tank A and B respectively) (below), along a 24h day.

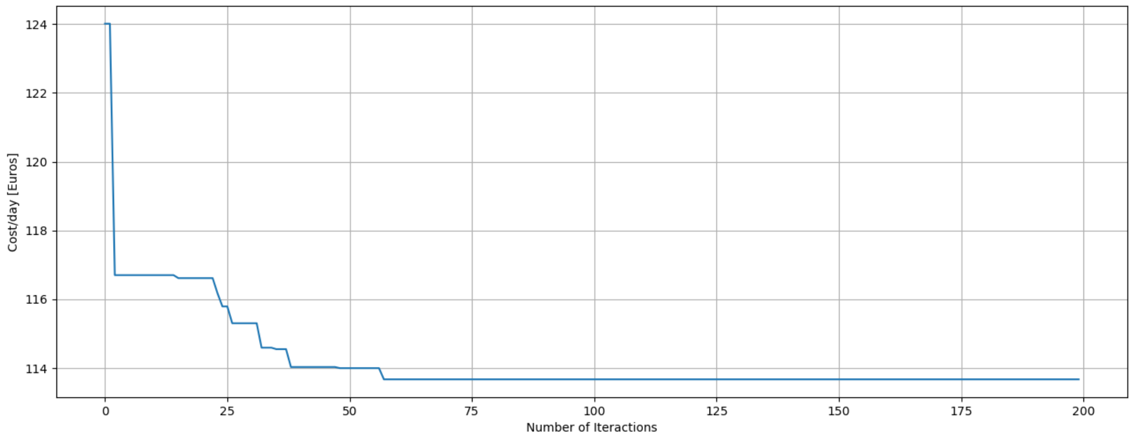

Fig. 8. Evolution of the pumping cost per day throughout the number of the algorithm interactions (generations).

It is common that tank levels tend to decrease throughout the day, following the higher tariff price. Note that the high tariff prices usually occur during higher water consumption rates in average. This means that when the electricity tariff is higher there is the preference for using the water stored to save pumping costs. Or, in other perspective, there is a preference in raising the tank levels, i.e. increasing the water storage, before the high tariff is engaged.

4. Conclusions

An optimization method to minimize the pumping costs in a water distribution network was successfully developed.

First, the water network is modelled in EPANET 2.0, which is responsible for evaluating the pump scheduling scenarios concerning the system feasibility (including the water demand compliance) and energy consumption.

Then a metaheuristic method, in this case a genetic algorithm, was developed in PYTON programming language and linked with EPANET 2.0. The optimization problem structure may be adapted for specific water network complexities in order to speed up the solutions convergence or improve the search technique.

In general, the water storage is crucial in water pumping cost minimization, specially by reducing pump operation during high electricity tariff prices. This is accomplished by controlling the pumping scheduling throughout the day.

The developed optimization algorithm achieves improved results as expected, and is able to accommodate more complex systems. For the tested case studies cost improvements of 10%-17% were achieved. Naturally these improvements depend on the original strategy implemented.