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Improving energy efficiency in water supply systems with pump scheduling optimization

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ABSTRACT

Water supply systems have a significant environmental and energetic impact due to the large amount of energy consumed in water pumping and water losses. The safe and efficient operation of these systems is crucial, where digital tools, such as monitoring, hydro-informatics, and optimization algorithms, are key approaches that can play an important role on support decisions.

This paper presents a hybrid optimization method to improve the energy efficiency of a water supply system towards a more sustainable water management concerning the water-energy nexus. A genetic algorithm was used to optimize the pumping schedule during the day. Knowing the water consumption *a priori*, it is possible to define the optimal pump status for a specific timeframe (e.g. every 1 h), minimizing the operation costs, and also the energy consumption and associated carbon dioxide emissions. Knowledge-based mechanisms, like introducing known feasible solutions in the population and selective mutation mechanisms, were introduced in order to boost the algorithm convergence. A model of the water network developed in the hydraulic simulator EPANET was used to evaluate the solutions. All the physical constraints of the water supply system (e.g. hydraulic compliances) and water demands must be met for each solution, including the level limits of the water storage tanks.

From the obtained solutions, it is found that optimizing the pump scheduling can improve the energy efficiency up to 15% in average (maximum of 25%) comparatively to the real operation, although this value can severely decrease if a conservative approach is assumed of maintaining more water stored in the tanks (low-risk approach). Similar improvements were achieved for cost and carbon dioxide emissions. Besides knowledge-based mechanisms, the analysis of the water storage risk was also an innovative outcome of this paper.

Finally, digital tools can be used to optimize the system with minimal investment in equipment or physical intervention, although optimal solutions depend on water availability, water demand, and water storage risk.

1. Introduction

1.1. Motivation

Water resources offer an important range of services that are crucial to a sustainable development. It's incessant demand has been largely influenced by population growth, industrialization, food and energy security policies, and growing production/consumption patterns. As such, the United Nations Sustainable Development Goals (especially Goal 6, 11 and 12) addresses specific actions that have the aim to ensure everyone's access to safe water, and improve resource efficiency including energy in water systems, cities, and sustainable consumption patterns (UN General Assembly, 2015). The energy consumption of the water sector worldwide accounted for 120 Mtoe in 2014, mainly in the form of electricity, corresponding to 4% of the total global electricity consumption. Water supply and distribution represent the largest share of energy consumption in the sector (IEA, 2016). The management improvement of these systems, in terms of energy and resource efficiency, is a crucial step towards a more sustainable use of water, and in general a more sustainable consumption and development strategy.

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Variables and nomenclature

Acronyms

AdA	Aguas do Algarve (water company from Algarve region)
AdP	Aguas de Portugal (National water company)
GA	Genetic Algorithm
GHG	Greenhouse gases
SWSS	Smart Water Supply Systems
WSS	Water Supply Systems

Symbols

d	day of the week (weekday, weekend, holiday), which influences the tariff
E	sum of the electrical energy consumed (kWh) by all pumps used, measured by EPANET
e_p	pumping energy efficiency per each pump used (p) (kWh/m^3)
h	time step, in hours
n	relative to a specific junction or node
p	relative to a specific pump
p_t^{max}	maximum number of pumps available for a specific tank (t)
s	season electricity tariff (Winter, Spring, Summer, Autumn)
t	relative to a specific tank
T	electricity tariff (Eur/kWh)
w	water flow (m^3/h)
w^d	water flow demand to the pump (p), node or junction (n), and tank (t) (m^3/h)
$w_{p,\ n,\ t}$	water flow throughout the pump (p), node or junction (n), or tank (t) (m^3/h)
w_t^l	water level in a specific tank (t), in meters
$w_t^{l,max}$	maximum water level allowed for a specific tank (t)
$w_t^{l,min}$	minimum water level allowed for a specific tank (t)

Genetic algorithm parameters

F	objective function (cost driven) concerning optimization
F^*	penalized objective function (cost driven) concerning optimization, used in the genetic algorithm
g	generation in the genetic algorithm loop
N	number of individuals of the population in the genetic algorithm
O_g	offspring population in generation g, in the genetic algorithm
Pop_g	parent population in generation g, in the genetic algorithm
v	decision variables which define the pump status (on or off) in method i), or how many pumps are switched on in method ii) (this was the method used)

Pump sets (described by its ID name) per tank

Tank A	BB046, BB047
Tank B	BB008, BB009
Tank C	BB068, BB069, BB070, BB071
Tank D	BB064, BB065, BB066, BB067

Water supply systems (WSS) are large-scale systems that transport water over vast geographical areas to the population, leading to significant environmental impacts, namely, a huge amount of energy consumption and associated greenhouse gas emissions in water pumping processes, and water losses. Electricity consumption associated to pumping systems represents the largest share of energy consumption in the entire water sector (IEA, 2016; Lam et al., 2017), which can reach up to 90% (Grundfos, 2004). Retrofitting the pumping equipment by introducing more efficient solutions, including the use of variable speed systems motors and introducing enhanced control systems, often allow significant energy savings (Marchi et al., 2012). Technological and non-technological innovative techniques will be essential to address water challenges and to keep the cost of the solutions affordable, as claimed by WssTP - Water Supply and Sanitation Technology Platform (WssTP, 2018), one of the European Technology Platforms (ETPs) initiated by the European Commission to focus on Research and Technology Development in the water industry. Accordingly, digital tools, such as system monitoring, hydro-informatics, data analytics, simulation, optimization algorithms, are key aspects that can play an important role in system efficiency and support decision in integrated water-energy frameworks.

In the Portuguese water company AdP Group, the water supply systems comprise 1152 intakes, 650 water pumping stations, 1726 reservoirs, 158 water treatment stations, connected by 17018 km of water ducts (Aguas de Portugal, 2016). In Portugal, around 59% of the operating costs corresponds to energy costs, mainly in the form of electricity used in the water pumping (AdP, 2016). Therefore, the target of water companies and municipalities is to guarantee the security of supply, but also to reduce the energy consumption costs and environmental impacts associated with the operation, i.e. aiming for a sustainable supply system.

Actions for improving the water sector sustainability has already been implemented by the AdP Group, such as implementing on-site renewable energy sources, contributing to the decentralization and diversification of electric energy production, i.e. using non-fossil energy sources. More actions are being considered such as retrofitting the system equipment, but this usually includes extensive economic planning and significant investments (Papagiannis et al., 2018), which sometimes is not desired. Another approach is to improve the pumping operation by enhancing the pumping control through optimization techniques. Digital and control techniques, e.g. monitoring, modelling, and optimization, have the advantage of not requiring major investments, system renovations or modifications, which sometimes becomes more attractive.

1.2. Literature survey

It is a fact that digital techniques are important aspects to be considered in the improvement of water systems. One of the most important approaches is water system modelling, which allows to create hydraulic simulations and evaluate distribution networks concerning system infrastructure design and feasibility, and water availability and demand patterns (Farina et al., 2014). EPANET is one the most used hydraulic simulators (EPANET, 2018), which is recurrently supported with add-ons continuously being developed, such as automatic network generators for system design (Muranho et al., 2012) or programming interfaces used in the interaction with optimization algorithms (Coelho et al., 2012).

With the aim to improve the efficiency of the water supply system operation, two optimization approaches are often considered: i) optimization of the water levels in the storage tanks; or, ii) optimization of the scheduling of the pumping operations. Both approaches may be relatively successful depending on the case study.

In the first case, the basic concept consists of triggering the pumps relatively specified water levels in the adjacent storage tanks. Pumps are switched on when the water in the tank reaches a minimum level and switched off when the water in the same tank reaches a maximum level. The selection of the optimal trigger levels in water tanks to control the pumping operation using genetic algorithms, and considering also the variation of the electricity price throughout the day, have shown to be successful in energy costs minimization, specially by increasing pumping during off-peak electricity tariff periods (Alvisi and Franchini, 2016; Marchi et al., 2017). These methods are often known by rule-based control optimization. In these studies, the use of optimized and variable tank levels saved 20% of the energy consumption when compared to fixed tank levels.

In the second case, the optimization of the pump scheduling aims to define the pump status throughout the day, i.e. defining if a specific pump is switched on or off at a specific time. Although the tank levels do not trigger the pump switches, the water is also maintained within specified tank levels. The application of metaheuristics for this kind of technique has shown to be promising from early (Mackle et al., 1995), where simple implementations have shown to achieve up to 8% of energy savings. Other studies also using a genetic algorithm, but in a more complex water network, have shown cost reductions of around 30% (Costa et al., 2010). An adaptive weighed objective function to solve the pump scheduling considering the electricity cost and also the pump maintenance costs has also been suggested (Abiodun and Ismail, 2013), which introduced an added complexity to the duration of the operation of each pump in the system.

The combination of optimal tank trigger levels and pump scheduling can also be used, and although this can advance improved energy savings it adds complexity to the algorithm an increases the computational burden. In some of these approaches different trigger levels are used during different periods of the day, aiming to reduce the pumping operation during the electricity peak tariff, but at the same time maximize pumping in the off-peak tariff period with improved scheduling schemes (Blinco et al., 2014; Kazantzis et al., 2002).

The selection of the decision variables structure is crucial in terms of convergence and computational time, either using the tank level triggers or pump scheduling approaches. A comparison of different representation schemes for the scheduling decision vector was performed in (López-ibáñez et al., 2005; López-Ibáñez et al., 2011). Despite optimizing the tank levels produce successful results, alone or combined with pump schedule, in this paper only the latter was used since the water company operators of the case study preferred to hold the control of the water storage.

Although the use of genetic algorithms or similar metaheuristics have shown in the previous studies to be suitable for water network optimization problems, some studies identified the necessity to improve the solutions convergence in large water systems applications. Hybrid methods such as modified mutation mechanisms and hill climbing methods were used within the main algorithm structure and were able to reduce the computation time (Costa et al., 2010; van Zyl et al., 2004).

In order to simplify the optimization problem most of the system characteristics are static. Nevertheless, the use of variable-speed pumps has proven to increase the system energy efficiency, which often includes the introduction of additional analytical models within the optimization method (Marchi et al., 2012). Similarly, considering pumps characteristic curves to select the best operation point has also been suggested in (Moreira and Ramos, 2013) reaching up to 44% of energy savings.

A different approach considering the implementation of renewable energies and its application also in industrial circuits was also already approached using a non-linear programming algorithm for the determination of the operational planning of pumped-hydro systems (Vieira and Ramos, 2008; Zhang et al., 2018).

Many studies refer to water supply networks optimization, and the results will naturally depend on the network complexity, water availability, water consumption patterns, and optimization method used. A review of the research challenges concerning simulation models and optimization approaches of water distribution systems is provided in (Mala-Jetmarova et al., 2017).

1.3. Contributions

In this paper, the authors propose to optimize the daily scheduling of the pumping operation of a specific WSS, while still meeting the water demand and considering the electricity tariff variation. The objective is to find the optimal operational sequence for each pump throughout 24 h (i.e. define when the pumps are switched on/off), in order to improve the water system management and the efficiency by reducing the energy consumption, CO_2 emissions, and costs. A platform integrating several digital tools such as monitoring, modelling, water consumption prediction, and system optimization were developed and applied to a real WSS. All the physical constraints of the water supply system and water demands are taken into account by the final solutions.

One of the innovative aspects of this paper is to provide two kinds of solutions: one solution exclusively focusing on the minimization of the cost/energy regarding the use of the pumps, and the other solution focusing on the latter objective but also considering to maintain the water storage in the tanks within safer levels (storage risk management). This highly influences the energy consumption in the system, as well as the water storage. Another innovative aspect of this paper is the hybridization of the genetic algorithm used to optimize the pump schedule with the introduction of several mechanisms to enhance the convergence and the solutions search method (see Section 4.4 for details), such as:

i. The implementation of a mechanism to improve the initial population sample, not only to supply a good random sample of candidate solutions but also by analytically find a few feasible solutions of pumping scheduling (not necessarily optimal) and introduce them in the initial population, helping the genetic exploitation operators;
ii. The implementation of a selective mutation operator, which acts only on non-feasible solutions, that analytically (and carefully) changes the decision vector towards a better search direction;
iii. The implementation of another selective mutation operator, which acts only on feasible solutions but which had their water tank levels depleted below a specified minimum, by analytically help the decision vector to find solutions with more levelled water levels (minimum variation between the initial and final water level in the tank) (see Fig. 1 to understand the limits).

1.4. Organization of the paper

This paper is organized into six main chapters. In the first chapter, Introduction, the water sector challenges are contextualized followed by a brief literature background where several

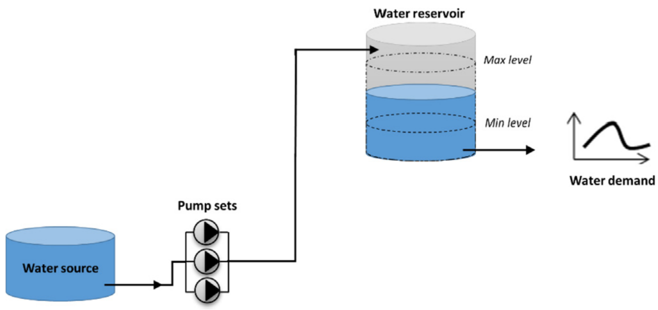

Fig. 1. A simplified example of a WSS with one water source, three pumps, and one water tank with specific water level limits.

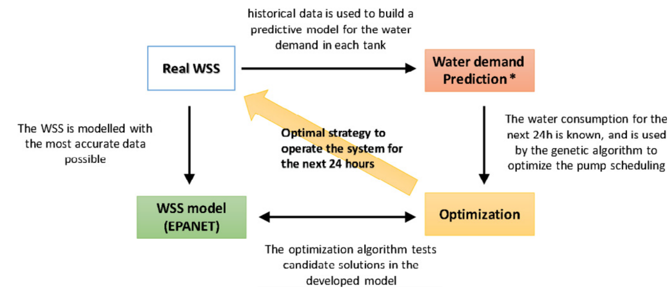

Fig. 2. Scheme of the main modules of the pump optimization framework.

optimization approaches applied to water networks are referred. In chapter 2 the pump scheduling problem is described in a more technical perspective. In chapter 3 the case study and the modelling approach are presented, followed by the optimization method in chapter 4. Finally, the results are presented and discussed in chapter 5 followed by the conclusions and future work in chapter 6.

2. Pump scheduling problem

A water supply network is mainly composed of reservoirs/tanks, nodes, and water pumps, in a simplified way (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).

The main objective of this work aims to answer the following question: *How can water management be optimized for increased efficiency, minimized environmental impact, and minimize costs?*

Important factors influencing the cost besides the pumping operation duration, are the electricity tariff structure and the efficiency of the pump sets concerning the pumping needs. 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, such as (see also Section 4.2):

i. Maintaining sufficient water within the system's tanks, or within specific levels, according to water demands;
ii. Water distribution network physical and hydraulic compliance (e.g. piping, pressure, or water levels restrictions);
iii. Pumps technological constraints.

Besides being important to the costs of operation, pumping scheduling optimization can also lead to further improvements, such as better response to periods of water scarcity.

Depending on the size of the water network, the number of pumps, nodes, and tanks, the modelling task of such system by analytical procedures may be extremely difficult. In these cases, although several models of water distribution systems are available, the optimization problem is still complex, and algorithms which depend on the full analytical formulation of the problem become almost useless for large networks. Therefore, many authors take a modern optimization approach, like using metaheuristic methods, similarly to the method presented in this paper. In such methods, the main advantage is that the mathematical formulation of the problem can be dissociated from the optimization algorithm (as further detailed in chapter 4).

In this paper the authors addressed the pump scheduling problem with the following steps (Fig. 2):

- **Diagnostics**: an audit was performed to the pumping stations, aiming for a detailed evaluation, determine hydraulic conditions, identifying inefficiencies in the system and determine the pump efficiency sets and deviations from the nominal values provided by the manufacturer. This sets the baseline scenario before any optimization.
- **Modelling**: the WSS is modeled in EPANET as is presented in chapter 3. This allows to evaluate scenarios and test several solutions.
- **Prediction**: a water consumption prediction model was developed based on historic data recovered by the water company AdA. This model allowed to predict future water consumptions, i.e. have the water consumption pattern for each tank for the next 24 h. Based on the water consumption pattern, it is possible to select the optimal scheduling for each pump (e.g. with the time step of 1 h). Although the prediction model development is out of the scope of this paper, the prediction data for a specific day was used in the optimization.
- **Optimization**: the proposed methodology for pump scheduling optimization is only possible having the water system model and water consumption prediction stages completed, as is presented in chapter 4.

All the above steps were part of a European I&D project, LIFE SWSS – Smart Water Supply Systems (please see http://life-swss.eu/en/for more details). In this paper, only the optimization is explored in detail.

3. Water supply system modelling

Modelling WSS aims to create a virtual idealization of the real water distribution network, by properly simulating the water hydraulics through the network piping, nodes, storage tanks or reservoirs and pumps. The main goal of a hydraulic simulation is to reproduce the best possible approximation of the real system behavior, and therefore, the accurate real data collection is crucial (performed by the water company AdP). However, and as mentioned before, connecting all these components and comprising with the water demand and physical restrictions of the system in order to obtain reliable simulations of a WSS can become extremely complex. Therefore, to model a WSS, the hydraulic simulator EPANET 2.0 was used due to its versatility (EPANET, 2018), as it is a public domain program and widely tested by the scientific community (Mays, 2000; Rossman et al., 1994; Yingying et al., 2018). An example of a WSS network implemented in EPANET 2.0 is schematized in Fig. 3. The main inputs required for a hydraulic simulation with EPANET 2.0 are concerned to real data and are presented in Table 1.

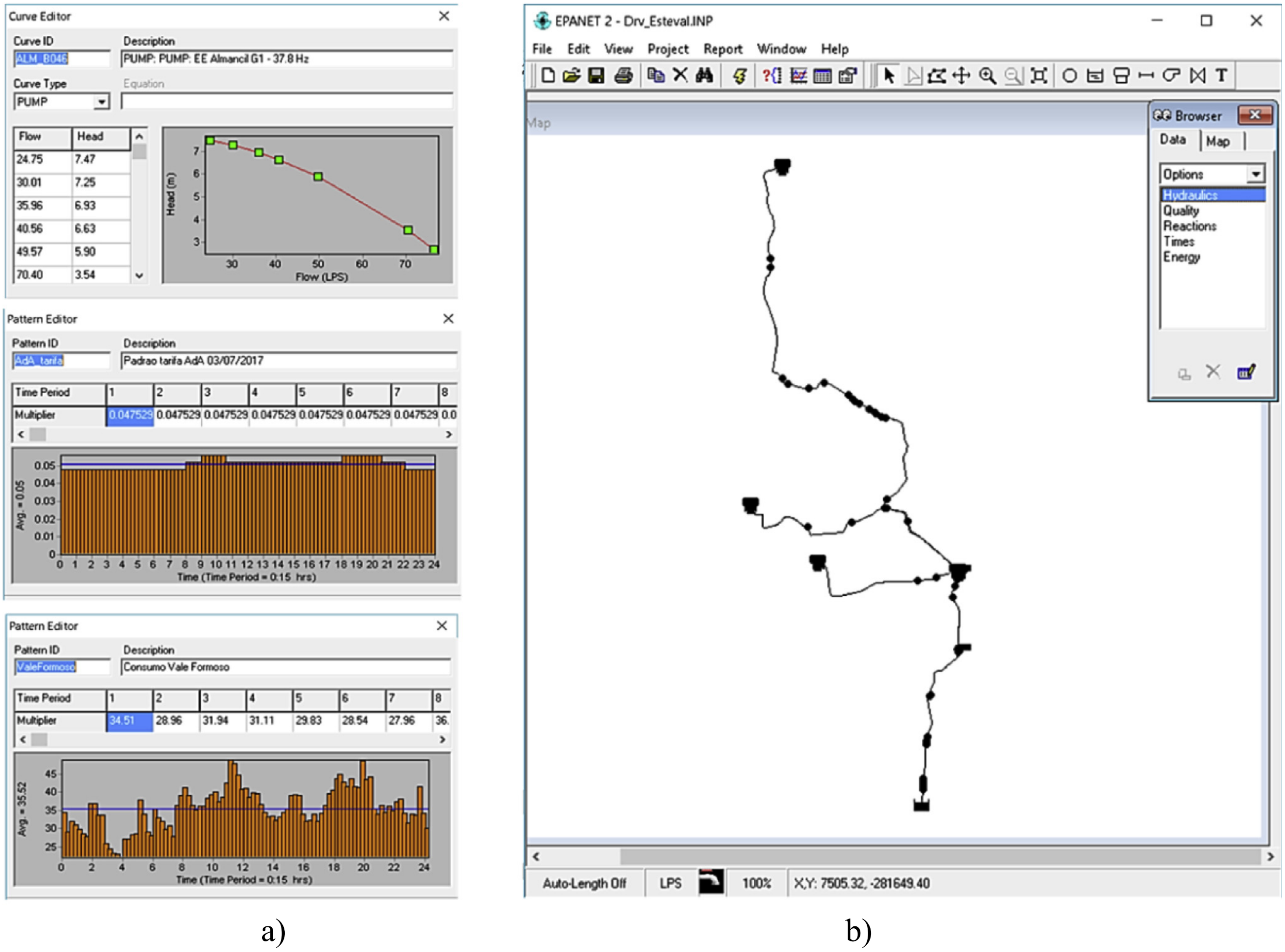

Fig. 3. Example of a hydraulic simulation of a WSS network of the using EPANET 2.0: a) the characteristic curve of one of the pumps, the electricity tariff, and the water consumption pattern in one of the tanks, b) the water network model.

Table 1
Main inputs required for a hydraulic simulation. * This data is used to model the real WSS from AdA (Fig. 4), which are remained confidential.

Inputs	
Variables	Description
physical characteristics and system components*	- terrain topography
	- pipes (length (m), diameter (m))
	- nodes and junctions (pipe connection)
	- pumps (capacity (m^3/s), power (kW), efficiency (%), characteristic curve)
	- tanks (diameter (m), height (m))
hydraulic constraints	- pressure limits (Pa)
	- water demand compliance
water demands	- water flow demand (m^3/s)
tanks initial conditions	- water level (m)
operation rules	- rules definition on when pumps should operate — usually, a pump switches on when the water in the respective tank reaches the minimum limit and switches off when the water reaches the maximum limit.
electricity tariff	- electricity price per period (Eur/hour/season)
Outputs	
- water flows (m^3/s) in every node, junction, pump, pipe section	
- tank levels (m) in every tank	
- operation costs (Eur) due to the energy consumption in the pumps	
- pump efficiency (kWh/m^3)	
- pump power (kW)	
- pump usage (%)	
- hydraulic constraints accomplishment (error alerts)	

3.1. Case study outline

In this paper, the case study belongs to AdA - Águas do Algarve (http://www.aguasdoalgarve.pt/), the water company from Algarve region in Portugal (Fig. 4). The case study is composed of four pumping stations connected to 4 storage tanks (each pumping station supplies water to each tank) (see Fig. 5). Tank 1 and tank 2 have set of 2 pumps each, and tank 4 and tank 5 have a set of 4 pumps each. Although there are 2–4 pumps in each set, the management of water supply network sometimes establishes that the best operational mode is alternating the pumps in operation avoiding the excessive continuous running of the equipment. Although sometimes this cannot be possible due to the water demand, the use of an alternating operation can reduce the wear of pumps and maintenance costs.

In the AdA system, the water demand in the summer is usually the double when compared with the demand in the winter. Sometimes, in the summer, because of high water demands, the management of WSS is very complex and difficult. To calculate the water demand for the next 24 h it was applied a prediction algorithm, that it is not within the subject of this paper (more info can be obtained in LIFE SWSS webpage). Moreover, the water in the storage tanks must be maintained within a specific minimum and maximum levels that were provided by the water operator as it is specified in Section 4.2.

In order to calculate the energy costs of the pumping stations, the electricity price (tariff) contracted by AdA was considered. The case study used for the optimization results regards to a weekday in July (3rd of July). However, the optimization results were compared with other days, namely, a Friday, Saturday, and a Sunday, which have different tariff values and different consumption patterns. Fig. 6 shows the different tariff structures.

4. Optimization method for pumping operation

There are several types of optimization methods which have been used to find optimal pump schedules. The water network modelling is analytically complex, and the optimization search space is neither mathematically convex, differentiable, or continuous, and there can be several different feasible scenarios. Meta-heuristic methods (such as genetic algorithms) have the advantage to be appropriate to solve this kind of problems. Although in cases with a certain degree of complexity the global optimal solution may not be found (which is a known disadvantage), the advantage is the ability to find good approximate solutions to the real optimum in a reasonable amount of time – very useful in large and analytically complex search spaces. Classic optimization methods can be used only in small-scale problems (and usually continuous search spaces), or with very simplified representations of the system. The modelling complexity itself can usually be surpassed throughout tools such as EPANET, used in this study (Section 3). Considering this necessity of modelling the hydraulic network, several optimization techniques are usually coupled with an existing hydraulic simulator, capable of validating network constraints (i.e. pipes, pressure, or water levels restrictions), testing solutions, and providing feedback to the optimization algorithm in order to readjust and readapt for the next iteration. Some examples of these algorithms coupled with EPANET, such as simulated annealing, genetic algorithms, and differential evolution, or even a branch and bound algorithms were used by (Carrijo et al., 2004; Costa et al., 2015; Sousa et al., 2006; Suribabu, 2010).

The genetic algorithm (GA) has been widely used in the scientific research community (Chipperfield et al., 1994), and has proven to be well suited to deal with these kind of problems (a few examples can be seen in some of the work cited above or in Section 1). A genetic algorithm is a search heuristic inspired by Darwin's theory of natural evolution, by reproducing the process of natural selection where the fittest individuals in a population are selected for reproduction in order to produce offspring of the next generation. The analogy lies in maintaining and evolving the solutions that are closest to the optimum, rather than the less optimal ones, while the diversity in the population is used to search the space for more solutions.

The pump scheduling can be approached as a parametric problem (where each parameter refers to the pump switching per hour, as detailed ahead) which suit very well within the genetic algorithm structure. The GA works using a chromosome structure (well-known terminology within genetic algorithms topic). The chromosome is composed by the decision variables which determines the state of each pump (on/off) defined per each time step (see Section 4.3). Each possible solution, known as an individual, is defined by a set of decision variables, i.e. the definition of the state of all pumps of the system for all time steps (24 h). A set of individuals assessed by the GA is known as the population. Several genetic operators are applied to the population which is iteratively evolved. The GA structure and application is presented in more detail in Section 4.3 and 4.4, while

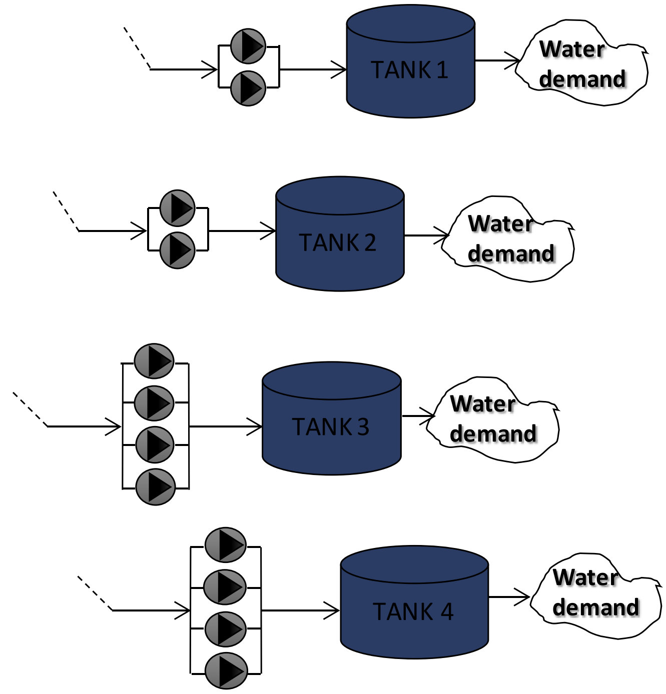

Fig. 5. Scheme of the case study presenting the water tanks and its associated pumps supplying water.

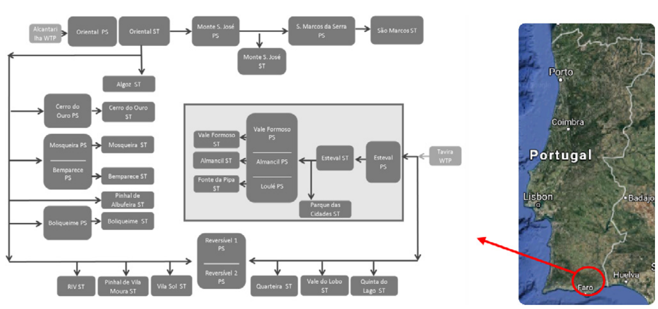

Fig. 4. Scheme (left) of the real water supply network in the Algarve region, Portugal (right). The squared area represents the used case studies. (PS – Pumping station (containing one or more sets of pumps), SP – Storage tanks).

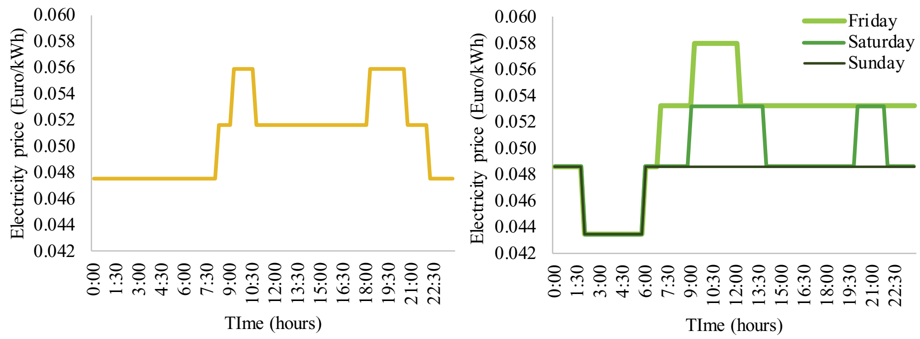

Fig. 6. Variation of the electricity tariff during the day, i.e. electricity price (Eur/kWh): case study (left), tariff used in the sensitivity analysis (right).

the objectives and constraints relative to the optimization problem are defined in sections 4.1 and 4.2.

4.1. Optimization objectives

The main goals are to improve the WSS energy efficiency, reduce CO_2 emissions, and reduce costs. Since energy and CO_2 emissions are directly linked to the energy consumed in pumping, then, when reducing the pumping operation costs all of these are being also reduced with special interest for water system operators (i.e. reduce costs). The optimization objective is to minimize the cost of operating the pumps (F) supplying the demanded water throughout 24 h (one day), as defined in equation set (1) to (5).

Objective function:

$$minimize: \quad F = \sum_{h=0}^{h=23} T(h,\ d,\ s)\, E(h,\ e_p,\ w_p) \tag{1}$$

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

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

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

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

where the used parameters are as follows:

- T – electricity tariff (Eur/kWh), that depends on the time of the day (see Fig. 6)
- h – time step, in hours, throughout 24 h
- d – day of the week (weekday, weekend, holiday), which influences the electricity tariff.
- s – season (Winter, Spring, Summer, Autumn), which influences the electricity tariff
- E – sum of the electrical energy consumed (kWh) by all pumps used, measured by EPANET for each solution. This will depend on the pump status (decision variables) per time step h (Section 4.3).
- p –each pump used, $p = 1$ to 12
- e_p – pumping energy efficiency per each pump used, p, (kWh/m^3). This depends on the water flow in the pump and on the pump head and speed (calculated in EPANET)
- $w_{p,\ n,\ t}$ – water flow throughout the pump (p), node or junction (n), or tank (t) (m^3/h)
- $w^d{}_{p,\ n,\ t}$ – water flow demand to the pump (p), node or junction (n), and tank (t) (m^3/h)
- w_t^l – water level in the tank (t). It must be between specified limits ($min,\ max$), specified in Section 4.2

The feasibility of the system is evaluated by the simulation model of the water network developed in EPANET (see Section 3). 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 event is very important and is included in the state information provided by the simulation model.

4.2. Constraints

Two types of optimization constraints were considered. One considering the water level within the storage tanks, and the second considering the hydraulic compliance of the system, which deals with pressure limits mostly (see also chapter 2 for a description of the WSS). For this specific case study, it was assumed that the water source has sufficient water to cover the demand and that the water demand for the next 24 h is known. The water level in the tanks (w_t^l) must be between the specified minimum and maximum limits (see equation (5)), which are [$w_t{}^{l,\ min}$, $w_t{}^{l,\ max}$]:

- Tank A = [1.8,5.10];
- Tank B = [1.8,2.85];
- Tank C = [1.8,3.75];
- Tank C = [1.8,4.60];

These limits were provided by the water utility that manage this case study - Águas do Algarve.

All the hydraulic and physical restrictions of the WSS network must comply, otherwise, the solutions will be discarded. These are determined by the simulator EPANET. If solutions comply with the hydraulic restrictions but fail to meet the tank level constraints, then the solution is not discarded but is penalized. The water level in the tanks is evaluated for each candidate solution, and a penalty factor is attributed to the cost value of a solution if it fails to comply with these constraints (equation (6)). The penalty factor is a weighted function so that faulty solutions are more or less penalized based on how much they deviate from the physical restrictions of the WSS network.

Updated objective function (F*) by a penalty factor:

$$F^* = F + \sum w_t^l(h), \quad \forall\ h \in \left[0,\ 24\right[\left| \left(w_t^{l,\ min} \geq w_t^l(h) \vee w_t^{l,\ min} \leq w_t^l(h) \right) \right. \tag{6}$$

4.3. Decision variables

There are several ways to define the decision variables, where some of which were already pointed in Section 1. Following the main structure of genetic algorithms (further detailed in Section 4.4), in this paper the decision variables are defined as the state of each pump during a specified time step, during a day, and are defined as follows:

Decision variables - Switch (on/off) of each pump, per hour, during 24 h. Although in equation (1) 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.

(Candidate) Solution - A combination of values, composing the decision variables, that specifies the schedule operation of the pump during 24 h.

In a genetic algorithm, the chromosome is the structure composing the decision variables. Each decision variable is also known as a gene. The set of genes forms the decision vector which is concerned to an individual or candidate solution. Two chromosome structures may be selected in the developed algorithm. Nevertheless, structure (ii) is the standard in the proposed method, and concerns to the presented results in Section 5:

Structure i).

If the number of demand points is higher than the number of pumps, then the chromosome may assume the shape as in Table 2 (and Fig. 7). This configuration is less complex than configuration ii), and the number of pumps is the most important parameter. The decision variables (v) are defined as 0 or 1 (switch on or off) per hour (h), per pump (p). Calculating the hourly pump scheduling, for 24 h (h), this simple approach produces $2^{p \times 24}$ possible combinations.

Fig. 7 shows an example of the structure i) considering 12 pumps and 4 tanks, leading to $2^{12\boldsymbol{x}24=288\ \boldsymbol{variables}} = 4.97 \times 10^{86}$ combinations:

Structure ii).

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 3. 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. In this case, the demand point will be the tanks itself. 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 (t) has its respective maximum number of pumps (p^{max}) associated (e.g. Fig. 8 represents 4 tanks with 12 pumps associated), plus the option of having all switched off. Calculating the hourly pump scheduling, for 24 h (h), this approach produces $(1+\boldsymbol{p_t^{max}})^{24}$ possible combinations per demand point.

Fig. 8 shows an example of the structure ii) considering 12 pumps and 4 tanks, where in tank 1 and 2 there are 2 pumps in each ($p^{max}=2$), and in tank 3 and 4 there are 4 pumps in each ($p^{max}=4$)), leading to $3^{24\ \boldsymbol{variables}} + 3^{24\ \boldsymbol{variables}} + 5^{24\ \boldsymbol{variables}} + 5^{24\ \boldsymbol{variables}} = 1.19 \times 10^{17}$ combinations.

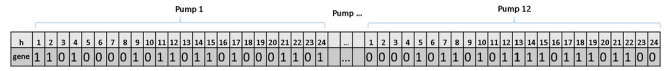

Fig. 7. Scheme of the chromosome structure i).

4.4. Hybrid genetic algorithm

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. 9. The main algorithmic structure is similar to that commonly used in genetic algorithms (Chipperfield et al., 1994; Goldberg, 1989), and is as follows. First, an initial population (Pop_g) is generated with N individuals (3), which are afterward evaluated (4). The initial population is generated randomly (1), or by selecting individuals known to produce feasible results (2) (this should be made carefully because it may accelerate the convergence but it may increase local optima issues) (see Section 4.4.1). Individuals that do not comply with constraints are penalized. Then, a selection procedure (5) selects a percentage of the best solutions to generate the offspring population (O_g) using crossover and mutation operators (6 and 7). Uniform crossover and creep mutation operators were used. Subsequently, the offspring population is evaluated (8) and a selective mutation procedure is followed for individuals having high penalty factors (9) – this aims to increase convergence (see Section 4.4.2). Afterward, these mutated individuals are evaluated and returned back to the offspring population (10), and the best individuals from the offspring population are reinserted (11) to the main population. The loop continues till a maximum number of generations (g) is reached. In this study, an initial population of 80 individuals and a total of 140 iterations were assumed to be reasonable after a few training runs, with a percentage of 25% for the offspring crossover and mutation. Table 4 resumes the main optimization inputs and assumptions. Most of these parameters were selected after several trials, and produce the best results within a reasonable time and computational time.

The hybrid feature of the algorithm aims to improve solutions and the convergence procedure, and is determined by two mechanisms: Knowledge-based population and the Selective mutation. Both of these mechanisms are knowledge-based procedures, meaning that information about the water network and respective limitations are used to locally improve or find solutions known to be feasible. These methods are known to be successful in large or complex search spaces (Costa et al., 2010; Syberfeldt and Persson, 2009; van Zyl et al., 2004), and are detailed in the following section. Although these methods can improve the convergence of the algorithm, especially reducing the search efforts throughout the

Table 2
Example of the chromosome structure i) used in GA, i.e. the decision variables throughout the time step h during 24 h of operation for a number of p pumps.

Pump (p is a specific pump)	$p=1$			…	p		
Time step (h - is the time step, which is a specific hour, $h\varepsilon[1-24]$, for each pump p)	$h_{p=1}=1$	…	$h_{\ p=1}=24$	…	$h_p=1$	…	$h_p=24$
Gene values (v - decision variables value (binary 0/1))	$v_{p=1}=0/1$	…	$v_{p=1}=0/1$	…	$v_p=0/1$	…	$v_p=0/1$
Meaning i.e. status of each pump (on/off)	on/off	…	on/off	…	on/off	…	on/off

Table 3
Example of the chromosome structure ii) used in GA, i.e. the decision variables throughout the time step *h* during 24 h of pumping operation for a number of *t* tanks (demand points) and associated pump sets.

Demand point (in this case the tanks *t*)	t = 1		… t	
Time step (*h* - is the time step, which is a specific hour, *h*ε[1–24], for each tank *t*)	$h_{t=1} = 1$	… $h_{t=1} = 24$	… $h_t = 1$	… $h_t = 24$
Gene values (*v* - decision variables value (integer value ranged by 0 and the maximum number of pumps available per tank p^{max})	$v_{t=1} =$ 0 to p^{max}	… $v_{t=1} =$ 0 to p^{max}	… $v_t =$ 0 to p^{max}	… $v_t =$ 0 to p^{max}
Meaning i.e. number of pumps on/off (0, 1, 2 … max num. Pumps p^{max})	number of pumps on	… number of pumps on	… number of pumps on	… number of pumps on

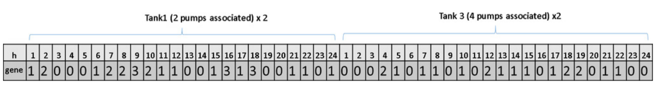

Fig. 8. Scheme of the chromosome structure ii) (note that tank 1 and tank 3 are repeated since they have equal representations of tank 2 and 4).
Note that structure ii) deals with fewer combinations of integer variables, which can be an advantage in terms of computational effort.

domain space, they should be used carefully since the risk of getting trapped on local optima solutions may increase. Therefore, its use in this study was performed with special attention to maintain a diversity degree in the population.

4.4.1. Knowledge-based mechanisms for improving solutions convergence

4.4.1.1. Knowledge-based population. The optimization module is initialized with N randomly generated candidate solutions. Nevertheless, since the complex water network has a large search space and may have only a few possible solutions, a mechanism was considered to analytically find a specified number of feasible solutions - although not necessarily optimal, it helps the genetic exploitation operators.

These feasible solutions are then mixed with the randomly generated solutions that compose the initial population. This hybrid approach is done carefully and the great majority of solutions that compose the initial population are randomly generated in order to avoid local minimum during the optimization process. In

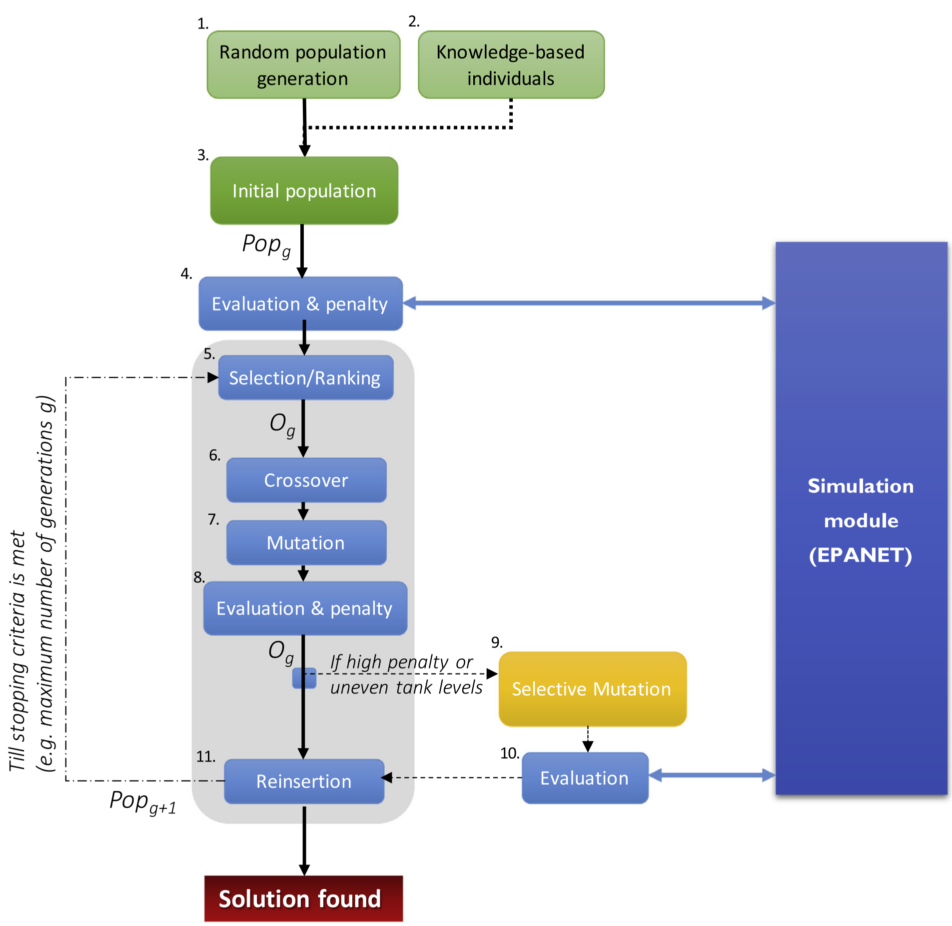

Fig. 9. Example of the algorithm structure.

Table 4
Main inputs required for the optimization algorithm.

Inputs	
Variables	Description
tank maximum limit level (m)	- final solutions must have the water level in the respective tanks within the limits, during all day – an optimization constraint.
tank minimum limit level (m)	
tank initial water level (m)	- for level driven solution i) the final and initial water level must be similar – an optimization constraint.
pump-tank association	- the number of pumps associated to each tank must be known in order to determine the genetic chromosome structure, i.e. the number of decision variables (as in Section 4.3)
time step (h)	- the optimization is defined for 24 h/day, with a time step of 1 h
number of generations (g)	- similar to the number of algorithmic iterations for genetic algorithms – 140 generations
population size (N)	- number of individuals or solutions that are evaluated in each generation – 80 individuals
elitism share (%)	- share of solutions that prevail unchanged after each generation
crossover share (%)	- share of solutions that will suffer crossover – 25%
mutation share (%)	- probability of a solution being mutated in order to add diversity and exploration in the search process – 10%

this study, two feasible solutions were aimed, each one selected by one different method. In this way, the initial population maintains diversity while a good exploration for convergence.

Two analytic solutions were then considered following two different approaches;

i. Electric tariff driven (cost driven) - With this approach, by knowing the off-peak electricity tariff periods, a solution containing pumps working during these periods is considered. However, since pumps working only during off-peak, may fail to comply with the required tank levels, the solution is then analytical analyzed and updated until a feasible solution for the network is found. This solution is considered to ensure that in the initial population, the off-peak tariff periods have some representation in terms of pump schedule during periods of the day, where a randomly generated solution may only provide partial useful information.
ii. Tank driven (level driven) - With this approach, the pumps are initially set to off during the 24 h period. Without pumping, due to demand, the levels in the tanks start to drop and once a minimal level is reached a pump is activated in order to keep the tanks levels above the minimum. The solution is then analytically analyzed and updated until a feasible solution for the network is found.

4.4.1.2. Selective mutation. The selective mutation occurs for every solution that is penalized, i.e. that is not feasible by not complying with the constraints or with the hydraulic rules. One mutation event occurs for such solutions for each generation. In this knowledge-based selective mutation, individuals with pumping schedules that lead to an excess of water in tanks, have some of their pumps switched off at the time steps at which the level limits are exceeded. On the other hand, individuals leading to lack of water in tanks, have some of their pumps switched on at time steps at which the level limits are not met. This method is reasonably simple, and its only aim is to accelerate the convergence of that particular penalized solution.

5. Results

One of the most successful approaches for optimizing the pumping schedule was to select an independent section of the whole water network (Fig. 4). The water demand associated with 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 the results of the optimization of the case study detailed in Section 3.1: a section with 12 pumps and 4 tanks. Note that, tank A and B have two pumps each, and tanks C and D four pumps each. The results are presented in Figs. 10 and 11.

Note that two solutions are provided:

- solution i) is a tank levelled solution, i.e. the optimization algorithm is driven to search solutions that minimize cost while at the same time, at the end of the 24 h, the water level in the tanks is maintained above its initial level (0 h);
- solution ii) is purely driven by cost minimization.

In order to minimize cost (as in solution ii)) there are two options, which can be considered together: the use of the pumps only when the electricity tariff is low, and the use of the water stored in the tanks). This is only possible if, during the period of the day with lower tariff, is sufficient for the pumps to deliver enough water to cover demand, and/or if there is enough water stored in the tanks to cover the demand and maintain tanks levels above a minimum limit. On the other hand, solution i) tries to use all the resources in solution ii) described before, but enforces the water level in the tanks to be above the initial level by switching on pumps to cover this constraint. Technically, in i) a constraint is added that measures the variation between the initial and final water level in the tanks, which if not fulfilled the solution is discarded (see Section 4.2).

The approach i) will have a higher cost in return of having more water stored in the tanks for the next day, and solution ii) will have the lowest cost but will have much less water stored. In this way, the two solutions provide a range of operation for the water company, which presents a trade-off between cost and the tank level risk as decision-support parameters.

The advantage of supplying these two solutions to the water utilities is that they can “gamble” with the risk associated with the tank levels, which are flexible. In winter the minimum tank limits are lower than in the summer since higher water demand is expected in the summer (the case study is located in Algarve region, an intensive touristic region in Portugal, with high seasonality, and lack of water). Then, the minimum limits must be at a safe level, storing water that ensures enough water supply in higher demand periods. In this way, the two solutions provide a range of operation for the utility company, which can use the cost or the tank level risk as decision-support parameters to operate pumps during the day. The use of a very safe or conservative level, i.e. a high minimum limit, ensures that the tank will always have a lot of water stored,

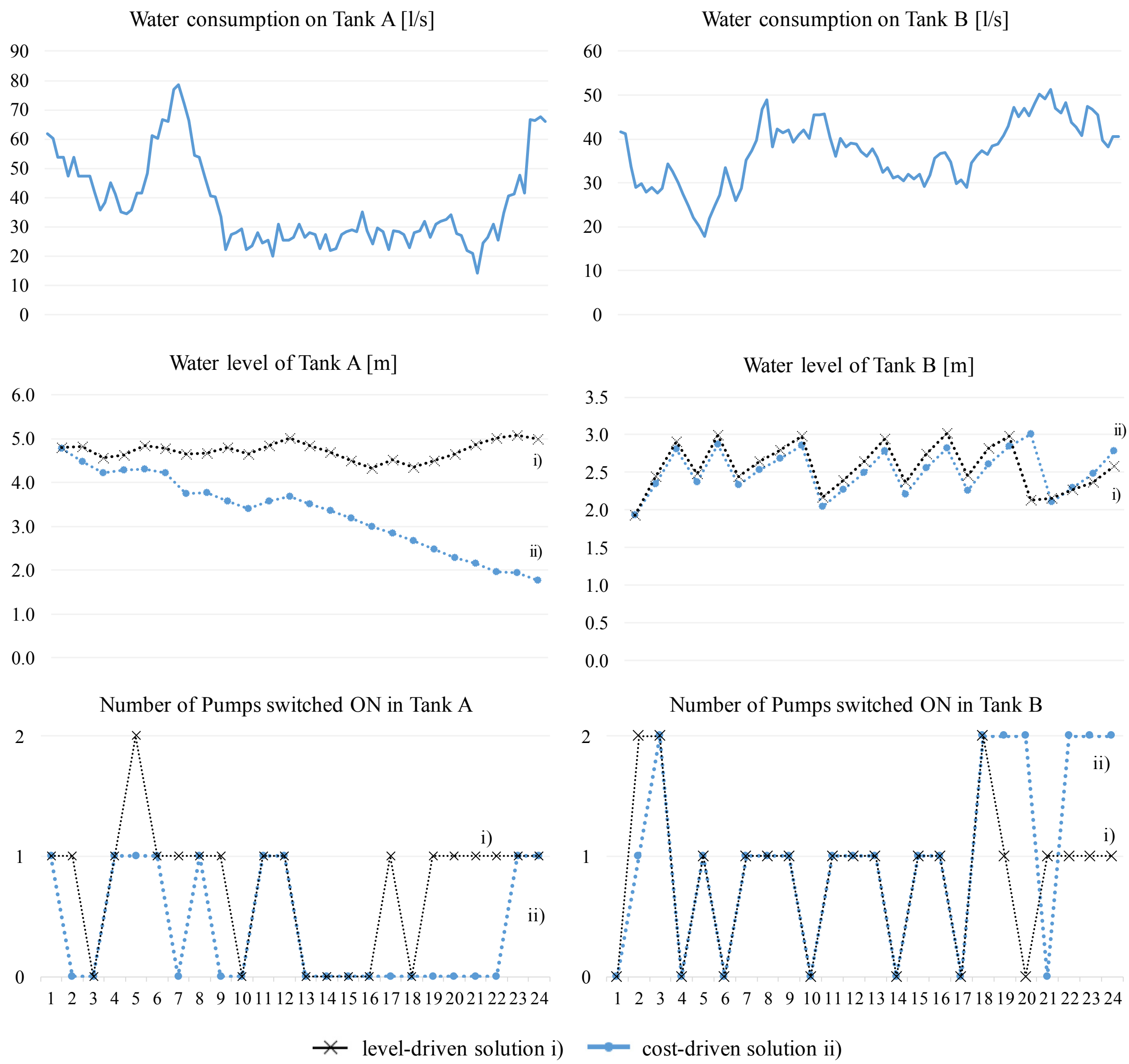

Fig. 10. a Water consumption pattern in each tank (above), water level in each tank for solutions i) tank level driven and ii) minimum cost driven (middle), and pump scheduling by defining how many pumps should be ON per time step (below). **b**. Water consumption pattern in each tank (above), the water level in each tank for solutions i) tank level driven and ii) minimum cost driven (middle), and pump scheduling by defining how many pumps should be ON per time step (below).

but will also lead to extensive use of pumping energy, and inefficient water management. On the other hand, using low minimum limits will allow the use of the pumps more efficiently, but there is the risk of not complying water demands in unexpected events.

Note that the high tariff prices usually occur during higher water consumption rates on average. This means that when the electricity tariff is higher there is a preference for using the water stored to save pumping costs. Or, in another perspective, there is a preference in raising the tank levels, i.e. increasing the water storage, before the high tariff is engaged.

The pumps were switched on or off for each 1 h time step (along 24 h), and in general, the tank levels were maintained at safe values within the minimum and maximum limits (Fig. 10) as these were inserted as constraints in the algorithm (Section 4.2). In what concerns to the hydraulic constraints or compliance of the system (e.g. pressures, flow demands, etc.), these were evaluated by EPANET, and only outputs without errors or compliance alerts were considered as final solutions candidates. Unfeasible solutions (or that fail constraints) can occur but these are only used to diversify the solution search, being posteriorly penalized. Therefore, the penalty function (Section 4.2) only interfered in the intermediate results during the optimization process to search for improved and feasible solutions.

Results show a reduction of the energy cost of 10% for the cost-driven solution in comparison with current operational rules used by AdA (see also Table 5). On the other hand, the level-driven solution represented an increase of 10% in comparison with the current rules but this is an expected result since this scenario has a more conservative approach by imposing that tank levels at the end of the day have to be at near the ones found at 0 h. Although this may increase the cost of the daily solution authors believe that it can reduce cost in the long run since it will reduce pumping over the following 24 h.

A typical convergence profile for metaheuristic methods can be seen in Fig. 11. The learning curve shows an improvement of around 5% during the search for the optimal solution. However, as mention previously, the initial population of individual solutions contains two feasible solutions although not necessarily optimal. This means that during the first algorithm iteration the best individual represents a cost saving of around 5% in comparison with the current operational rules. During the following iterations and during the exploratory search for the optimal solution an additional 5% were obtained, contributing for the total 10% improve.

The evolution of the pumping cost shows that further improvements could be attained if a higher number of iterations were considered since the learning curve maintained constant for only 15 iterations (125 and 140) until the limit of 140 imposed. By analyzing the learning curve its noticeable that solutions took up to 24 iterations until further improvement, reinforcing the idea that further improvement could be attended by using a higher number of iterations. Nevertheless, due to computational time, the algorithm was truncated to a total of 140 iterations.

Fig. 12 shows the results specified per pump, namely, the pump usage percentage during the day, the cost, and the energy consumed per unit of volumetric water flow. It is possible to observe that both solutions, cost-driven, and level-driven, used the same number of pumps for each tank, however, the level-driven shows a longer use in average which contributes to its higher daily cost. As mentioned previously this is mainly due to the fact that this solution has a more conservative approach by imposing that tank levels at the end of the day have to near the ones found at 0 h. For tank D, for example, results showed that it was not necessary to use the four pumps available, contributing to a cost reduction. The average energy use differences between solutions do not deviate significantly from each other.

In all cases, the pump selection within pump sets (composing the pumping stations) is performed post-optimization. This means that in events where more than one pump is switched on, the specific pump to switch on is determined externally to the optimization algorithm. In order to reduce the impact of maintenance, a rule is applied: a single pump should not be working continuously during large periods, such as a whole day. This is mitigated by using a pump rotation scheme, even in events where more than one pump is required.

In Table 5 a resume of the daily results is presented for the baseline scenario (using AdA rules) and the two optimized

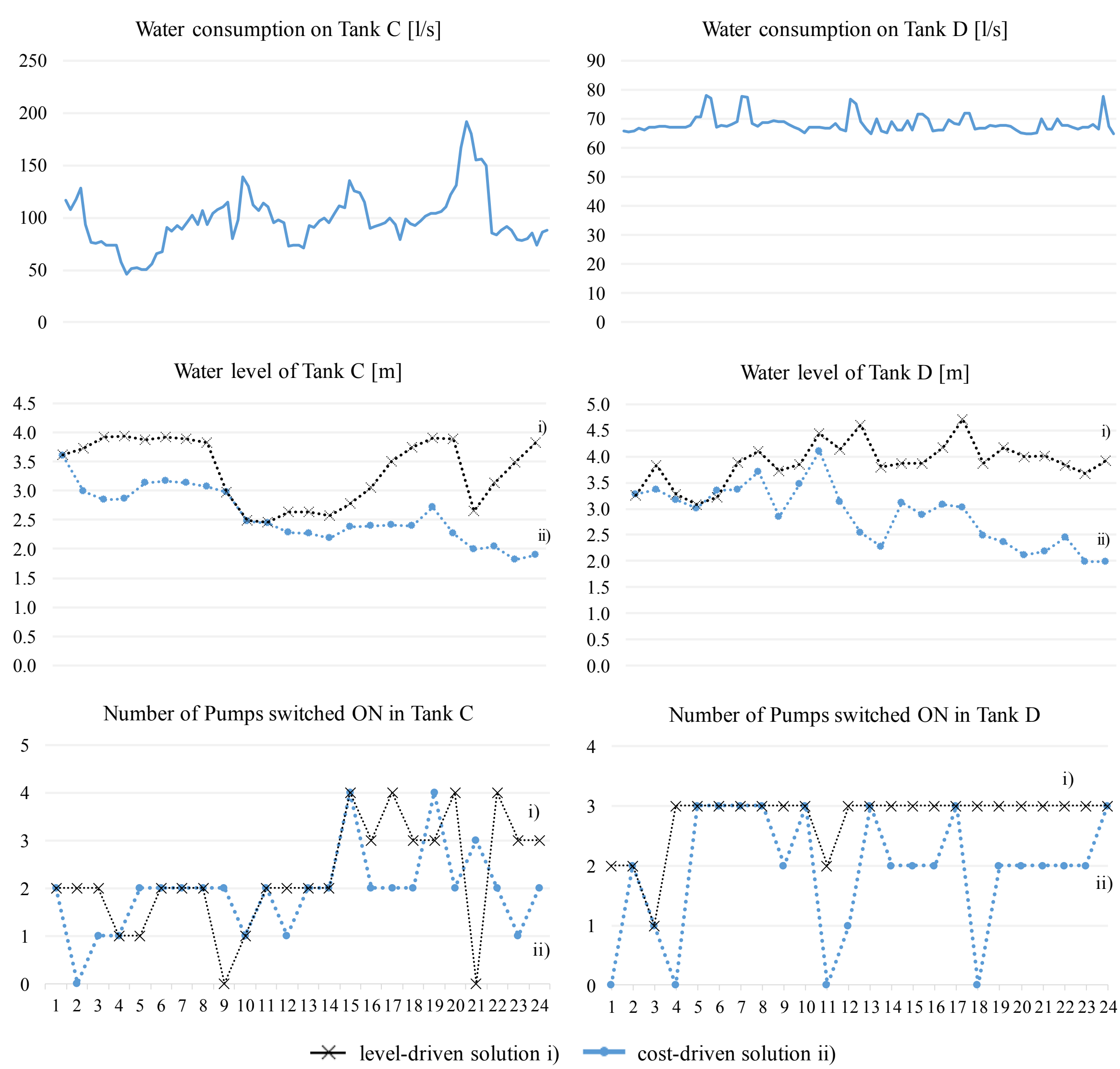

Fig. 10. (*continued*).

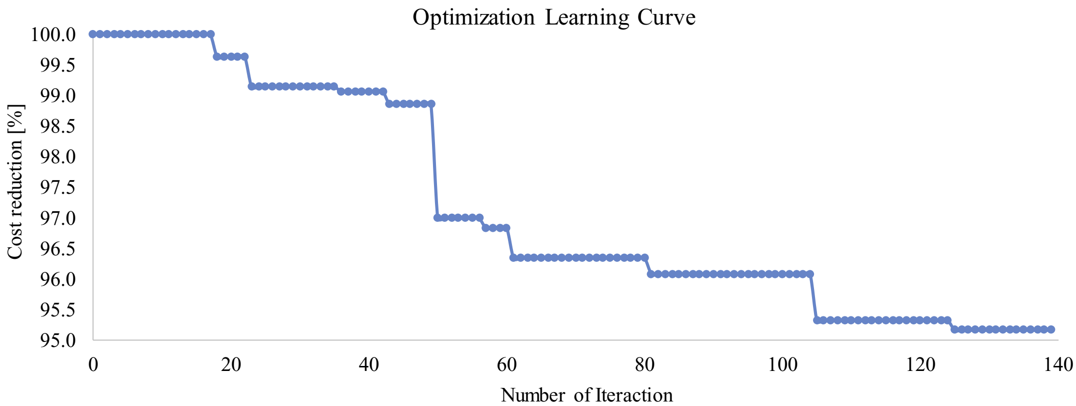

Fig. 11. Evolution of the pumping cost per day throughout the number of the algorithm iterations (generations).

Table 5
Resume of the daily results for the baseline scenario and the two optimized solutions.

	Cost (Eur/day)	Average energy consumption (kWh/day)	Average CO_2 emissions (kg/day)
Baseline	299.31	5895.29	2410.29
Solution level-driven i)	332.91	6565.89	2684.46
Solution cost-driven ii)	271.81	5346.61	2185.96

solutions. Note that as explained above, the level-driven solution i) seems worse than the baseline scenario, however, it ensures a secure level of water in the storage tanks which is a desired characteristic. Besides cost, the energy consumption and CO_2 emissions associated can be reduced up to 10% per day.

The pump scheduling problem, as expected, depends greatly on the water stored at the tanks, predicted water demand, and electricity tariff. All these variables (see tariff in Fig. 6) are different for different days, namely four patterns may be encountered, Sunday, Saturday, Friday, and the rest of the weekdays. Although the optimization results regard to a weekday, Table 6 presents a resume of the application of the same optimization method for different days of the week showing similar conclusions concerning the obtained solutions. On one hand, the cost minimization driven solution ensures the best results although the tanks levels are depleted to their lower limits; and on the other hand, the level driven solution stores more water in the tanks with higher costs in average (although it may achieve interesting results overall).

The exploitation potential of the presented methodology can be pushed to larger water supply networks, and also industrial circuits. This is mainly due to the modular structure of the optimization framework. Naturally, the larger the network is, the more complex are the dependencies between the decision variables and system/hydraulic constraints. In this case, the sectioning the system becomes a probable requirement.

6. Conclusions

A hybrid genetic algorithm was successfully developed to optimize the pumping scheduling of a water supply network aiming to minimize the energy consumption and costs. The optimization algorithm, developed in PYTHON was linked with the hydraulic simulator EPANET 2.0 which enabled to model the water network of the case study and evaluating the pump scheduling scenarios concerning the system feasibility (including the water demand compliance).

- One of the innovations of the optimization method is the introduction of knowledge-based solutions (solutions known to be feasible) to improve the algorithmic convergence by reducing the search efforts throughout the domain space. Nevertheless, this technique should be used carefully since the risk of getting trapped on local optima solutions may increase, and special attention to maintain a diversity degree in the population should be taken.
- Another innovation was to account with the trade-off between cost and the risk of the water level in the tanks as decision-support parameters to operate pumps during the day, i.e. two solutions were provided: a tank levelled solution, driven to minimize cost while at same time maintain the water levels in the tanks above a specific level; and a solution purely driven by cost minimization. The first approach achieves higher cost in return of having more water stored for the next day, and the second solution achieves the lowest cost possible but will have much less water stored.
- For the tested case study initially with an operating cost of 299.31 Eur/day, an energy consumption of 5895.29 kWh/day, and associated CO2 emissions of 2410.29 kg/day, improvements of 10% in energy efficiency were achieved, which is a positive advance for sustainable water management systems. Overall, it is found that optimizing the pump scheduling can improve the energy efficiency up to 15% in average (maximum of 25%) compared to the real operation; although this value can severely decrease if a conservative approach is assumed of maintaining more water stored in the tanks (low-risk approach). Similar improvements were achieved for cost and CO2 emissions.
- The obtained improvements depend on the baseline strategy implemented, on the water availability in the system (seasonal issue), the water demand, and on the water storage risk level assumed. In general, the water storage is crucial in water pumping cost minimization, especially by reducing pump operation during high electricity tariff prices. As such, potential improvements of up to 25% were identified for different days tested (with different electricity tariff and water demands) if considering full cost minimization, or up to 6% if considering tank levelled solutions (although this solution may also achieve cost increases as referred before).

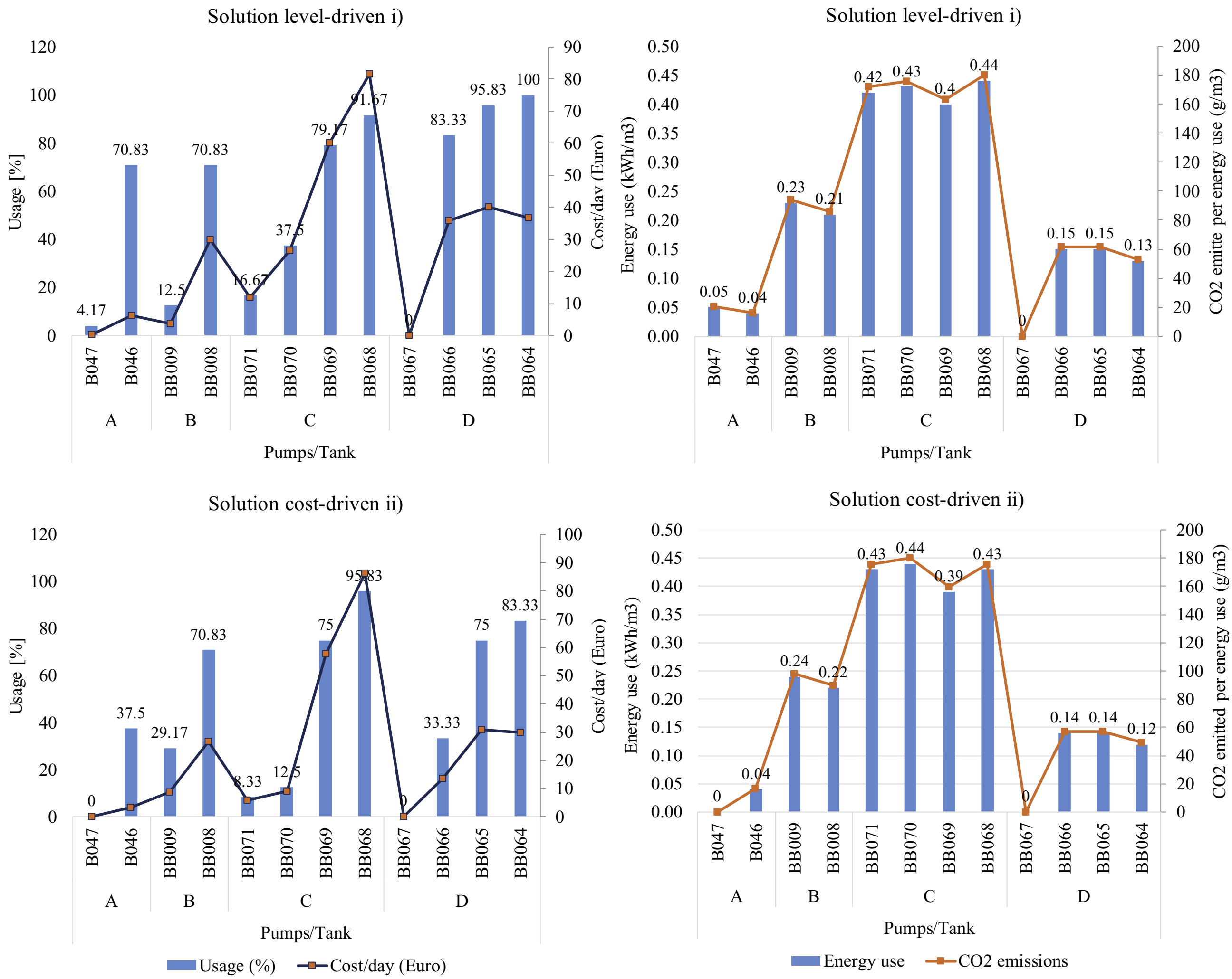

Fig. 12. Daily operation of each pump for solution i) tank level driven (above) and ii) minimum cost driven (bellow): pump usage percentage (left, bars), energy costs (left, line), specific energy use (right, bars), and CO_2 emissions (right, line).

Table 6
Resume of the daily results (cost and final tank level) for the baseline scenario and the two optimized solutions, for three different days.

			Tested days		
			07/07/2018	08/07/2018	09/07/2018
			Friday	Saturday	Sunday
Baseline	baseline cost (Eur/day)		264.64	245.47	234.54
	Initial tank levels (m)				
	Tank A		5.07	4.96	4.92
	Tank B		2.25	2.34	2.37
	Tank C		2.53	3.36	3.42
	Tank D		4.36	3.15	4.24
Optimized solutions	Solution level-driven i)	Cost (Eur/day)	248.59	249.93	248.59
		Final tank level (m)			
		Tank A	5.18	5.2	4.71
		Tank B	2.32	2.54	2.29
		Tank C	2.65	2.64	3.43
		Tank D	3.55	3.02	4.21
	Solution cost-driven ii)	Cost (Eur/day)	199.64	228.48	199.64
		Final tank level (m)			
		Tank A	2.92	1.86	2.4
		Tank B	2.03	2.61	2.64
		Tank C	1.83	1.89	1.84
		Tank D	2.5	2.35	2.17
	Comparison of the costs to the baseline operation (%) [Solution ii)/Solution i)]		−25.6% to −6.1%	−6.9%−1.8%	−14.9%−5.9%

6.1. Future developments

The exploitation potential of the proposed methodology can be pushed to larger scale systems, larger water supply networks, and also industrial circuits due to the modular structure of the optimization framework. However, in order to engage more complex systems with success, machine learning techniques may also be assessed to model the system and bypass the increased computational burden of testing and search for feasible solutions. This is being actively addressed by the authors for future work. In order to be well accepted by water industries, the development of this kind of methodology can never ignore the networks performance and resilience to real-time events. For instance, if the water consumption prediction fails regarding the real consumption, the optimization algorithm must adapt dynamically to the new conditions and supply solutions on-time. This issue is also being engaged for future work. Finally, multi-objective algorithms such as NSGA-II may be interesting to study to solve energy minimization and water storage maintenance simultaneously as a multi-objective optimization problem.

Acknowledgments

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