Water Supply System Operation Optimization to Reduce Energetic Costs

João Granate
Instituto Superior Técnico
joao.granate@tecnico.ulisboa.pt

Water supply systems have become very inefficient due to population growth and increasing demand. To accommodate these changes, an immediate need for these structures was created and many systems were design with considerable faults. These faults create leakages, lack of pressure, incorrect pipe diameters, inefficient operations or deterioration within the pipes, leading to energy efficiency decrease. This problem has been widely studied and some of the solutions found include : i) pipe sizing optimization; ii) variable speed pumps; iii) pumps replacement; iv) operations optimization. Of the aforementioned the least-cost alternative is the optimization of operations. The most effective way to optimize these operations is through the optimization of the pump schedule. By optimizing the schedule of pumps according to tariff, we can guarantee that not only the costs will be lowered, but the energy efficiency will improve as well.

To solve the pump switching problem, an algorithm was created and paired with an hydraulic simulator software in order to minimize costs and the wear of tear of pumps.This was done by using surrogate methods to decrease both the number of pump switches and the amount of hours pump work continuously. For this an Evolutionary Strategy optimization technique was used using python, paired with the EPANET simulator. The main goal is to provide data to perform a trade-off analysis between wear and tear of pumps and the overall cost of the WSS energy consumption.

***Index Terms*—water supply systems; genetic algorithms; evolution strategy; pump scheduling optimization**

I. Introduction

Water supply systems (WSSs) have been a crucial structure in human life. Unfortunately, due to population growth and the need to make water available to everyone, WSSs became greatly inefficient in the last century. This inefficiency leads to great energy expenditures and water leakages, meaning high unnecessary costs and ecological footprint.

In order to minimize such inefficiencies, researchers have studied different ways of optimizing water supply systems, ranging from pipe rehabilitation, or variable speed pumps, to operations optimization. Although structural changes could mean greater changes in terms of water leakages, and maybe overall system efficiency, these techniques imply high costs and time.

On the other hand, a widely studied alternative that eliminates structural changes, is to optimize the operations within the system. As it will be further discussed in sec. 2, water supply systems have pumps,tanks, valves and pipes, with pumps representing a great percentage of the system's energy use. These pumps have the purpose of pumping water to the tanks which is then, pumped into our households with a certain pressure. In the last few decades, the pumping of tanks has been developed into working automatically, meaning that pumps work autonomously with the help of constraints or a predetermined schedule. Therefore, optimizing the scheduling of pumps, would ultimately raise the system's efficiency and lower costs. This happens, because peak and off peak tariffs exist, meaning that pumping water into tanks has a different cost throughout the day. For this, computational optimization algorithms have been used in order to obtain the better strategy possible for water supply systems. Another phenomenon that contributes to inefficiency is the wear and tear of pumps, which tends to damage the pumps over time bringing their performance down. For this it is important to extend pump's life cycle and therefore reducing the WWS's maintenance costs.

However, as an optimization problem, pump scheduling is seen as very difficult to solve because of its large search space, high computing requirements and nonlinear and discontinuous nature of real-life networks. To develop a robust and accurate model, data collection on the physical network is needed, as well as a calibrated hydraulic model, demand information, the definition of a performance criteria and a set of constraints. In addition, because of its strongly practical nature, it is difficult to know which techniques work better in a general perspective, as most solution approaches are very specific, and might not be suitable for others.

In this paper an algorithm that optimizes the pump scheduling of the AdA case study was created, an Evolutionary Strategy algorithm paired with the hydraulic simulator EPANET 2.0. this algorithm has the goal of optimizing the the WSS energy costs while reducing the wear and tear of pumps using different surrogate methods.

This chapter is divided in four chapters, an historic review of WSSs will be made, followed by a description of the motivation behind this work, as well as the objectives of this paper and finally the structure of this paper will be presented.

A. *Motivation*

Water supply makes up for 4% (Amádis Santos 2018) of the world's total energy, meaning that any enhancements in terms of energy efficiency will have a huge impact on a larger scale, as it comprises a significant chunk of the world's global energy. With savings studied to be around 20-30%

(Feldman 2009) , having a huge economical impact on society. Nowadays other factors can be studied other than the cost. This approach offers other goals such as environmental issues (Xevi & Khan 2005), water quality (Farmani et al. 2006) or system's wear and tear(De Paola et al. 2016) allowing trade-offs to be studied, and optimizations to have more impact on different levels.

In terms of literature contribution, this is a widely studied problem for many years and still no consensus has been achieved due to the specific nature of all approaches. By including maintenance costs constraints on this optimization, we hope to contribute further into this area, in addition to the already studied minimization of pump switches this strategy will look to diminish the time each pump stays on continuously, which is not a widely studied subject.

B. Pump Scheduling problem

The pump scheduling problem, can have numerous approaches regarding its representations and requirements within the supply system. This has been a widely debated problem, as many studies have been conducted and no consensus has been found yet. The increasingly complexity of WSS makes it a more demanding problem, as the search space keeps growing and growing, as well as the energy tariffs which influence this problem in terms of economical challenges.

There are mainly two different representations of pumps available, implicit(Kazantzis et al. 2002) and explicit (Wu et al. 2001).

Explicit representation, specify the status of pumps on a time frame, with a predetermined schedule. This idea helps guaranteeing that tanks work accordingly with tariff hours, making sure that they are emptied during peak hours(low tariffs) and replenished during off peak hours (high tariffs).The pumps are represented as discrete variables, usually by binary coding (0/1) representing the off/on state of the pump for each time frame (usually 1 hour) of the whole testing schedule (usually 24 hours). These systems, are a very effective way to deal with this problem, but there are many complexities related. The need for demand forecasting and continuous optimization in order to keep calculating the best schedule within each time frame makes it more difficult to implement.

Implicit representation, on the other hand, works in parallel with tank levels. A predetermined water level for filling and emptying the tank is presented and throughout a certain time frame, pumps work in accordance with those water level. For example, when water reaches a low level the pumps would then work in order to fill the tank, as the water level rises, after reaching a predetermined height, the pumps would stop working until the water reaches low levels again. This leads to continuous variable as opposed to discrete, as the intervals are non-binary variables, although this is a viable option, usually the schedule is transformed into a discrete one. Although this helps the system maintain optimal tank levels, this technique alone cannot guarantee that water pumping is in compliance with tariff scheduling, making this a less effective method on a cost point of view.

However (Alvisi et al. 2016), techniques using both implicit and explicit representation have been used, pumps are activated by water levels, but a predetermined calculated optimal schedule, only allows pumping to be made according to the tariff. This eliminates the problems relative to implicit representations, with papers showing good results. This technique increases the complexity of the system, as well as search space, as in addition to work with tank levels, the algorithm will also have to calculated optimal scheduling according to demand forecasts and tariffs.

Another issue regarding this problem is related to the wear and tear of pumps (De Paola et al. 2016). In order to minimize the deterioration of pumps, leading to replacement or constant maintenance, some problem formulations include a limit of pump switches per time frame. This limit, not only leads to less pump usage, but also narrows the search space.

Different methods can be used to achieve the best possible pump operation schedule depending on information and time available. Not only energy costs can be lowered, but with the pairing of different techniques, welfare of pumps can be managed better, to ensure longer working pumps

II. Literature Review

Over the years different approaches to the optimization of WSSs have been made.

The earliest approaches show mathematical models without computational methods (Mala-Jetmarova et al. 2015), but as the years progressed with the introduction of digital computers, iterative models started being used. These included linear programming (LP)(Alperovits & Shamir 1977) and nonlinear programming (NLP) (Su et al. 1987) The biggest advantage of these type of optimization include its simplicity and easy implementation. The LP is able to produce globally optimal solutions, however, it is very limited, as with the increase of complexity it starts to become inefficient. On the NLP, more recent studies have been carried out (Vieira & Ramos 2008) that produce good results, but they are highly dependent on initial conditions making them less reliable, having a risk of falling into local optimal solutions.

With the introduction of heuristic and meta-heuristic algorithms, this field gained a different dimension as these types of algorithms were able to capture the immense complexity of this problem. Evolutionary algorithms (EA) have shown to be the dominant approach on this problem . Based on the Darwinian principle of evolution, with the principles of genetic inheritance and mutation, this type of algorithm is able to produce near-optimal results, subject to a large array of constraints and variables. The genetic algorithm (GA) is the most commonly known, and is more research in regards to the pump scheduling problem ((Cheung et al. 2003), showing great results. Another great advantage of these EAs is the fact that they can include multi-objective optimization, which allows to minimize various objective functions simultaneously, which has been successfully applied to the pump switch problem (Cheung et al. 2003), to study the trade-offs between different optimization domains. The drawbacks of these EAs is the fact that the solutions used may not be the globally optimal solutions and with large search spaces it usually leads to slow convergence, translated into high computational efforts dependent.

Other types of nature-based algorithms include Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO). The PSO is based on the behaviour of flocks of birds or swarms of fish to find food. It is population-based algorithm that starts with a random solution called particles, which fly through the search space with velocities that are dynamically adjusted according to their historical behaviour, hence, having the tendency to fly towards the better and better search space at each stage of the process. This technique as showed to produce good results when applied to the pump scheduling problem and can as been implement with a multi-objective approach (Al-Ani & Habibi 2012), aiming to reduce both costs and number of pump switches. The ACO is based on the behaviour of ants. The path followed by the ants depends on a chemical substance called pheromones, ants release these substances as they move and others follow the possible paths based on the amount of pheromones. This substance works as a communication mechanism and a reinforcement learning process (López-Ibánez et al. 2006). Various applications of this problem have been used over the years on the pump scheduling problem , obtaining good results. However, when it comes to pumps' wear and tear its not highly as used.

Other algorithms used include, the Simulated Annealing (SA), Harmony Search Algorithm (HSA). The SA is is based on the physical annealing of molten particles, starting at high temperatures and cooling down until its solidification, and uses probabilistic techniques to approximate the global optimum of a given function (Kirkpatrick et al. 1983). This algorithm shows a good performance overall, but shows high computational times. The HSA is musically inspired algorithm has attracted scientific interest.The HSA is based on the music performance process, where musicians search for the better state of harmony . It is a less researched and relatively new algorithm when compared to others, but shows great results and is able to perform a multi-objective analysis on the pump's wear reduction (Kougias et al. 2012).

When it comes to the maintenance perspective of the problem, various multi-objective analysis can be found (De Paola et al. 2016), but these are difficult to implement and very complex. A simpler approach using surrogate methods, by penalising solutions that show a number of switches above the limit, can be found (Dai & Li 2015), which also enables to study the trade off between lowering the wear of pumps and the cost. However this strategy does not include the lowering of hours pumps stay on continuously, which can incur in wear and tear.

III. Case study

In this paper, the case study presented belongs to AdA (http://www.aguasdoalgarve.pt/), the water company from the southern region of Portugal, Algarve. This case study network is comprised of 4 tanks, Vale Formoso (VFS), Almancil (ALM), Esteval (ESV) and Loulé (LLE). Tanks ALM and VFS have two pumps connected each, B046 and B047 for the first and BB008 and BB009 for the second. And the other tanks are supplied by 4 pumps each, BB068, BB069, BB070 and BB071 for ESV and BB064, BB065, BB066 and BB067 for LLE. This can be schematically represented by fig. 1. Although the number of pumps is 2 to 4, the management of the water supply advises that pumps should be alternating between them and avoid excessive amounts of consecutive hours running, a situation that cannot always be avoided . The demand was provided by the ISQ company, and was calculated by applying a prediction algorithm for the next 24 hours, that is not within the subject of this paper. This is a smaller part of the entire AdA network, showed on fig.(aguas do algarve). By working on a smaller scale with independent demand, we can diminish the complexity of the problem while still showing its relevance by being applied to a real life case scenario.

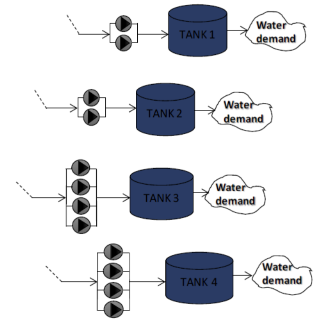


Fig. 1: Schematic representations of the water tanks and and associated pumps (Luna et al. 2019)

Although the number of pumps is 2 to 4, the management of the water supply advises that pumps should be alternating between them and avoid excessive amounts of consecutive hours running, a situation that cannot always be avoided . The demand was provided by the ISQ company, and was calculated by applying a prediction algorithm for the next 24 hours, that is not within the subject of this paper. This is a smaller part of the entire AdA network, showed on fig. 2. By working on a smaller scale with independent demand, we can diminish the complexity of the problem while still showing its relevance by being applied to a real life case scenario.

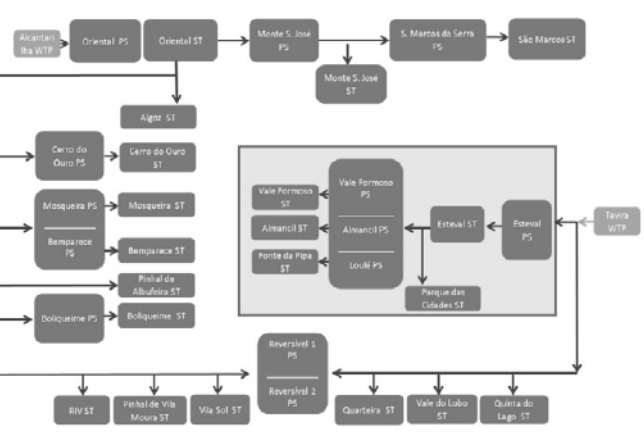


Fig. 2: Schematic representations of the whole AdA WSS with the case study part being highlighted (Luna et al. 2019)

The baseline is calculated by multiplying the amount of hours each pump stays on by the tariff at each hour, obtaining a baseline cost of 299.31 and a consumption of 5895.29 kwh/day. The tariff was provided by the AdA company and can be consulted on fig. 3

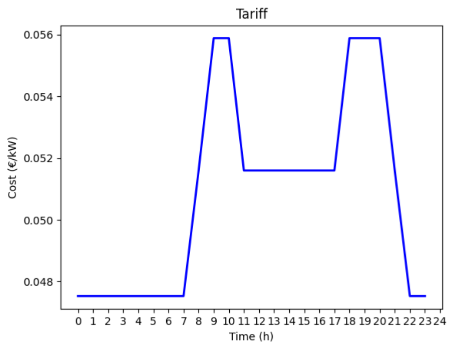


Fig. 3: Tariff in euros along the day

There already exist a GA implementation on this case study, with two different scenario approaches which will be presented in the next section of this paper. The first one, cost driven shows a result of 271.81 and a consumption of 5346.61 kWh/day, and the tank level driven one of 332.91 and 6565.89kWh/day.

IV. Methodology

A. Cos Function and Constraints

As previously explained the cost function is constructed by multiplying the on states of each pump by the tariff at that hour, as shown by 1. However depending on the scenario, the sets of constraints each objective function is subject to is different. It is assumed that the demand is met for both scenarios.

$$minF = \sum_{h=1}^{24} [T(h).E(h, e_p, w_p] \tag{1}$$

with the parameters:

T- electricity tariff(Eur/kWh) (fig.**??**)
h- time step in hours (24 hours)
E- electrical energy consumed (kWh)
p- pumps
e_p - pumping energy efficiency per each pump, p (kWh/m^3). Depends on pump head and speed calculated on EPANET
$w_{p,\,n,\,t}$ - water flow (m^3/h) throughout pump (p), node (n) or tank(t)

The first scenario is a cost driven approach, where the goal is to minimize the cost subject to hydraulic constraints evaluated by the EPANET, in regards to the physics characteristics of the network, tank level constraints and depending on the approach, a pump switch constraint and a maximum number of hours working continuously for each pump.

The second scenario is a tank level driven scenario. This strategy is used on a level trigger perspective of the pump switch problem. This means that instead of aiming to find the best cost by pumping at off peak hours, the pumps are turned on and off according to tank levels, to ensure that by the end of the day the tank level is equal or higher than the initial level. This is a more conservative approach as expectantly tends to higher the prices, but on terms of robustness of the WSS tends to produce better results. This is due to the fact that in case the demand raises unexpectedly for the next day, the initial water level is higher, which enables to respond better to demand fluctuations. To translate this to a mathematical language, in addition to the constraints shown above, a constraint on the difference of the water levels at the end and beginning of the day was created, to guarantee that the water at the end of the day is higher or equal than ate the beginning.

When it comes to hydraulic constraints, they are evaluated by EPANET and if they are not complied with the solutions are removed meaning that they can not be used. They are shown below from eq. 2 to 4 we can see those constraints, which ensure that the demand is met on both scenarios.

$$w_p(h) \geq w_p^d(h) \tag{2}$$

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

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

- $w^d_{p,n,t}$ - water flow demand to the pump (p), node (n) or tank (t) (m^3/h)

The tank limits were provided by AdA with a tolerance of 7%:

- Tank ALM = [1.8, 5.1], with tolerance= [1.674, 5.457]
- Tank ESV = [1.8, 4.6] , with tolerance= [1.674, 4.922]
- Tank LLE = [1.8, 3.75], with tolerance= [1.674, 4.013]
- Tank VFS = [1.8, 2.85],with tolerance= [1.674, 3.049]

If the candidate solution is below or above the tolerance levels, a weighted sum penalty constraint will be applied to the solution. This constraint and penalty can be seen below on eq.5 and eq.6.

$$w_t^{lmin}(1 - tol) \leq w_t^l(h) \leq w_t^{lmax}(1 + tol) \tag{5}$$

$$P_w = \sum w_t^l,\, \forall\, h \in [0, 24[\colon (w_t^l < w_t^{lmin} \vee w_t^l > w_t^{lmax}) \tag{6}$$

w^l_t(h)- water level (m) at a certain time step h
w^{lmin}_t- minimum water level allowed on tank t (m)
w^{lmin}_t- maximum water level allowed on tank t (m)

When it comes to the pump switch constraint and the number of hours working continuously, they work similarly. In these we have to input a limit of N for the switches and M for the hours. When it comes to pump switches it is also important to define what constitutes a pump switch. Every time a pump goes from an off state to an on state a pump switch has happened, this can be demonstrated by fig. 4 that shows a scheme of that process. Every time those two limits get breached, a penalty is added with a fixed value of 1000.

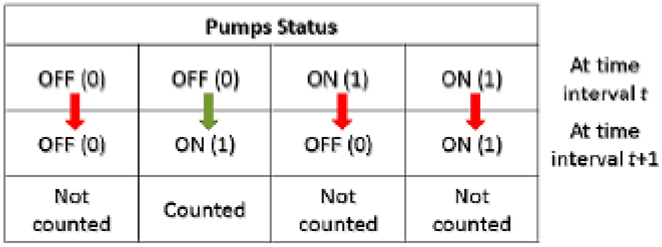


Fig. 4: The Mechanism of Counting Pump Switches (Al-Ani & Habibi 2012)

Every time those two limits get breached, a penalty is added with a fixed value of 1000. Both constraints and penalties can be shown below from eq. 7 to eq. 10:

$$NS_p = \sum_{h=1}^{24} (|p^{h+1} - p^h|) \, \forall \, p^h = 0 \tag{7}$$

$$P_N S = \sum_{p=1}^{12} NS_p, \, \forall \, NS_p > N \in \mathbb{N} \tag{8}$$

$$HW_p = max \sum_{h=1}^{24} (p^h + p^{h+1}) \, \forall p^h = 1 \;\; \& \;\; p^{h+1} = 1 \tag{9}$$

$$P_H W = \sum_{p=1}^{12} HW_p, \, \forall HW_p > M \in \mathbb{N} \tag{10}$$

NS- number of pump switches per pump p
p^h- pump state(on/off) (0/1) at time step h
P_{NS}- number of pump switches penalty
N- number of pump switches limit

HW- maximum number of hours a pump works continuously
P_{HW}- maximum number of hours a pump works continuously penalty (Eur)
M- number of hours a pump is allowed to work limit

The penalty regarding the initial and final level is also a weighted sum, that compares the initial water level with the final one and penalizes solutions based on how low the final level is when compared to the initial. It is important to highlight that this penalty is only applicable on a tank level driven scenario as it does not show the best possible cost. That constraint can be shown below along with is penalty function, from eq. 11 to eq. 12:

$$D^* = W_t^l(23) - W_t^l(0) \tag{11}$$

$$P_D^* = \sum_{t=1}^{4} D \, \forall D \neq 0 \tag{12}$$

D- difference between the tank level(m) at the beginning and end of the day for each tank
P_D- water tank difference penalty function

Finally, both updated cost functions with the penalties included, can be shown below on eq.13 and eq.14 for both scenarios.

- Cost 'minimum' function:

$$minF = \sum_{h=1}^{24} [T(h).E(h, e_p, w_p] + P_w + P_{NS} + P_{HW} \tag{13}$$

- Cost 'conservative' Function:

$$minF = \sum_{h=1}^{24} [T(h).E(h, e_p, w_p] + P_w + P_N S + P_H W + P_{D*} \tag{14}$$

B. Decision variables

In this problem the decision variables are defined as the state of each pump (on/off) during a specific time step (1 hour) during a full day (24 hours). To better understand this it is important to understand what defines a pump state. As previously shown in section I, there are different ways to represent a pump state. In this problem the explicit representation was chosen, in order to minimize costs according to the tariff, and not according to its tanks level. For this, discrete variables were chosen to represent the pump state. To do so, binary code (0/1) represents the pump state, where 1 indicates the pump is turned on and 0 indicates the pump is turned off.

After presenting our pump state representation, it is important to talk about the solution. This problem's solution is the pump switch schedule of a full day (24 hours). It includes the state of each pump (p), at a certain time step(h), in a full day (24 hours). The solution includes 12 pumps and 24time steps, leading to 288 binary values. In tab. I, we can see how the schedule for a pump on a single day is represented.

Hours	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
Pump State	on	off	on	on	off	off	off	off	on	on	on	on	off	off	off	on	off	off	on	on	on	on	of
Binary code	1	0	1	1	0	0	0	0	1	1	1	1	0	0	0	1	0	0	1	1	1	1	0

TABLE I: Example of one pump's schedule in one day

C. Evolution Strategy

Evolution strategies are search algorithms inspired by the principles of biological evolution. They belong to the class of evolutionary algorithms that take upon optimization problems by iteratively implementing small stochastic variations to a possible solution. In each generation (iteration), new offspring (candidate solutions) are generated from their parent solutions (already visited candidate solutions),via genetic crossover , their fitness is evaluated, and the best offspring are chosen to became the parents for the next generation. In addition to these solutions usually undergo mutations in order to avoid local optimum spaces.

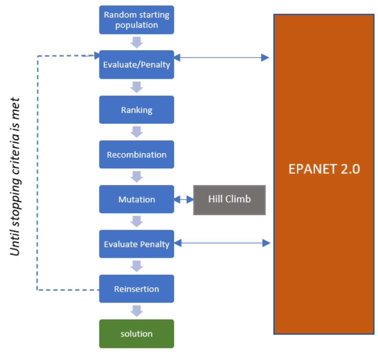


Fig. 5: Example of the algorithm structure

This algorithm starts with an initial population of 10 individuals random individuals (1). Each individual is then subject to the penalty constraints (2), being penalized accordingly and evaluated by EPANET, afterwards the solutions are ranked (3) according to their fitness (cost). The best solution is then chosen to perform crossover (4) with other solutions with a probability of 0.3, this happens via discrete recombination, where real life values can be used instead of binary ones and the crossover points are done randomly, generating one offspring. There is also a probability of solutions to undergo mutation (5), which on this algorithm is done as a hill climbing step, where solutions jump to a vicinity solution, with this happens with a rate of 0.7. Afterwards the new solutions are evaluated(6) by the penalty constraints and the EPANET to access their feasibility. The feasible solutions are then reinserted on the population (7). This process is repeated until a stop criteria is found, reaching a final solution (8). This algorithm contains two stopping criteria, the first one happens if the algorithm is not able to produce better results. From each 500 solutions generated the algorithm compares the current best solution to the new best, if that value is lower than 20, it computes a no gain occurrence, and after 10 no gain occurrences the algorithm stops. The second is reached once 10000 have occured. It is important to highlight that once a criteria stop is found, the algorithm resets and starts running for the tank level driven scenario, providing two solutions. On fig.5, an example of this process can be found.

When it comes to the chromosome representation, representing each solution by the example provided on table I constituted a really high search space having a total of 4.97 x 10^{86} possible combinations, having two pump states (1/0), 12 pumps and 24 hours (2^{12x24}). To save computational effort a more complex representation was used. In this representation, decision variables are the total pump states at each time step. This means that at each time step, the gene value ranges from 0 to the maximum number of pumps (p) that supply that tank(t), representing the number of pumps switched on at that moment, with 0 meaning that all the pumps are switched off. This leads to a chromosome like the one in fig6. When it comes to the search space, this leads to $(1+ p_t^{\mathbf{max}})^{24}$ possible combinations for each demand point. As there are 4 demand points (4 tanks) and with 2 tanks being supplied by 2 pumps each and the other 2 by 4 pumps each, leads us to $3^{24} + 3^{24} + 5^{24} + 5^{24} = 1.19 \text{ x } 10^{17}$ possible combinations, significantly less than the previous structure. This leads to a great advantage in computational effort as it was previously mentioned it narrows the search space considerably. This process can be shown on fig.6.

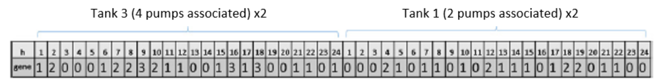


Fig. 6: Chromosome II scheme (tank 1 and 3 are repeated as tank 2 and 4 have the same representation) (Al-Ani & Habibi 2012)

V. Results

A. Preliminary Results

This ES was paired with EPANET. The learning curves can be shown below on fig.7 for the minimum cost scenario and fig.8 for the water tank level scenario. The algorithm takes a total time of 5959 seconds, a relatively high computational effort, with 5912 iterations needed for the cost driven scenario and 6278 for the levelled tank driven scenario.

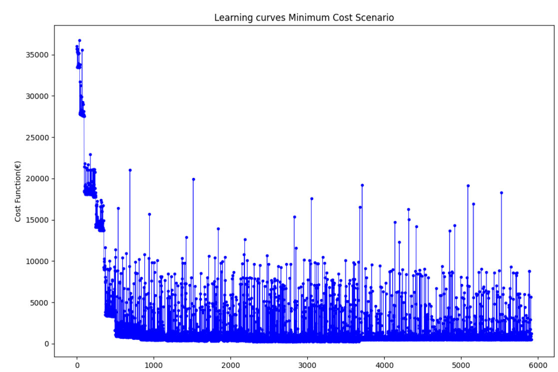


Fig. 7: Number of solutions until the algorithm stops

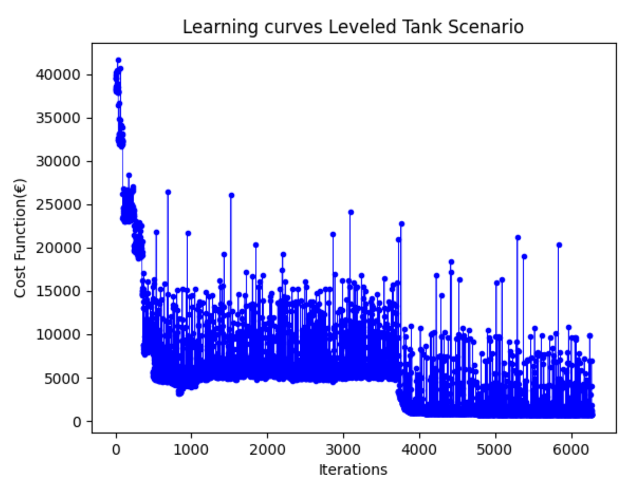


Fig. 8: Number of solutions generated until the algorithm stops

When it comes to results, in comparison with the results from the GA, the ES shows an improvement of approximately 10%

on the minimum cost scenario, and of approximately 21% when compared to the baseline cost. However, when it comes to the levelled tank driven scenario, a comparison can not be made as there is a constraint violation on the tank limits that raises the cost. When it comes to power consumption, on the ES the minimum cost strategy consumes approximately 4938 KW/h a day, which proves to be an improvement of approximately 8% when compared to the GA, and 19% when compared to the baseline. The results can be shown below.

The results can be consulted on the table below:

	Cost (€)	Energy consumption (kwh/day)
Baseline	299.31	5895.29
GA (minimum cost)	271.91	5346.61
GA (water tank level)	332.91	6565.89
ES (minimum cost)	246.61	4859.57
ES (water tank level)	693.69	5959.64

TABLE II: Results Obtained by the ES in comparison with the baseline and the GA

By looking at the tank level we can explained the results obtained above.

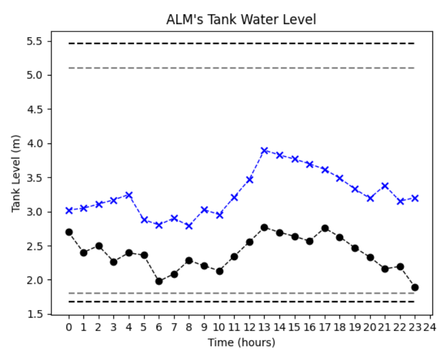


Fig. 9: Tank level throughout the day on tank ALM

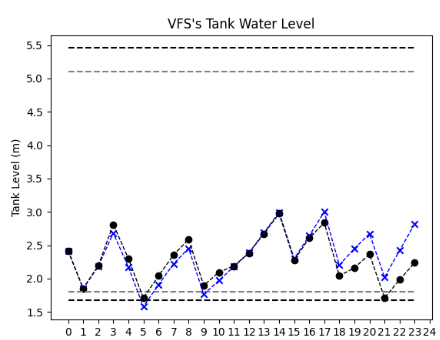


Fig. 10: Tank level throughout the day on tank VFS

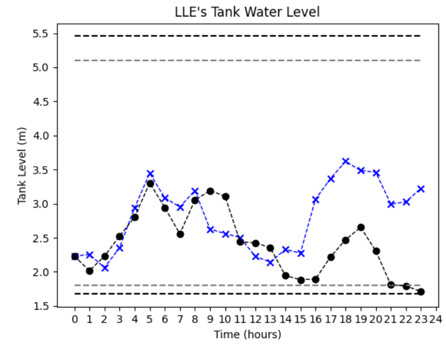


Fig. 11: Tank level throughout the day on tank LLE

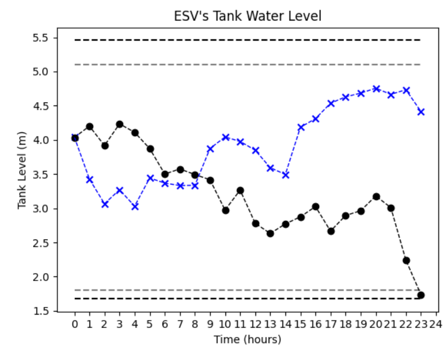
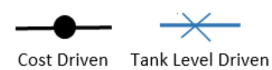


Fig. 12: Tank level throughout the day on tank ESV



The tank levels from each tank can be shown from fig.9 to fig. 12. Here we can see the compliance of the solutions with the tank level constraints. On a tank limit perspective we can see that on tank VFS the minimum tolerance limit is breached, incurring on a penalty which explains the high cost obtained by the ES. We can also observe that on a tank level driven scenario the tank level at the end of the day is always higher than the initial, showing that on this level the algorithm is working properly.

Overall, the ES shows good results when it comes to the minimum cost scenario, but is unable to find non-penalized results when it comes to the tank level scenario. The performance shows big computational times.

B. Pump switch constrained values

After assessing the initial results of the Evolutionary strategy we proceeded to apply the pump switch limit constraint. We started with a limit of N=7 pump switches, and lowered that limit until 1. The results showed that the total number of pump switches was decrease over as the limits got lower, until it got higher at the lowest limit due to the fact that after a solution has surpassed the limit, that pump tends to allow more switches than the initial levels as the penalty is not a weighted sum. These results can be shown below in fig. 13

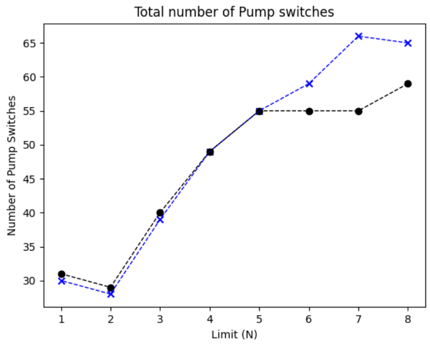


Fig. 13: Number of pump switches per limit N

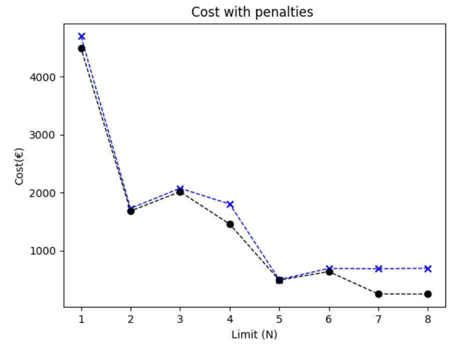


Fig. 15: Penalized cost per limit N

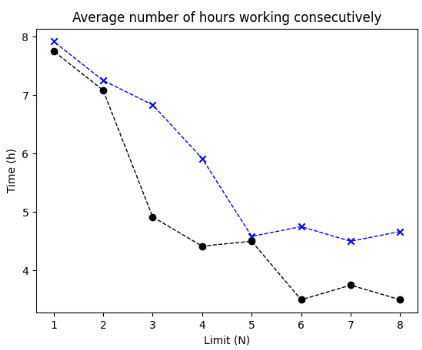


Fig. 14: Average number of hours pump work continuously per limit N

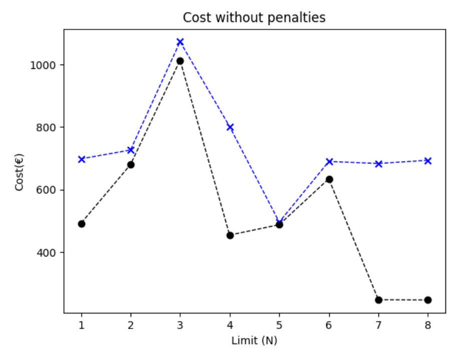
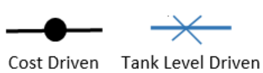
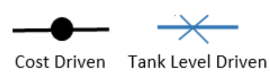


Fig. 16: Penalized cost per limit N





To see how this strategy influences the number of hours pumps work continuously, we decided to look at the system's average amount of hours per pump at each limit N. The results showed that in order to comply the low number of pump switches the pumps had to stay on for longer periods of time which could contribute to the wear and tear of pumps, as towards the end the values tend to be high. These results are represented in fig. 14, where there is a clear tendency for this value to grow bigger as the limits are lower.

When it comes to the costs this approach generates, we decided to study both penalized and non-penalized costs. The penalized costs shows the tendency of the algorithm and the non-penalized costs regarding the pump switch allows to study the energy consumption cost and compare different results, because, even if they do not comply with the pump switch limits, they can still prove to be better options than the current. Nevertheless, we decided to include tank limit constraint penalties as these solutions are worse than the non-penalized ones. The results can be shown below, where we can see that, overall, the algorithm struggles to find tank level feasible solutions, however it is able to find a tank level approach cost of 490.92 with all the limits being complied with, which could mean that by limiting the search space, the algorithm might have the tendency to produce better results.

The results can be further assessed on table III where along the cost and the consumption we can see the total number of pump switches and the average number of hours pumps stay on.

C. *Final Results*

Finally in order to reduce the number of hours pumps stay on continuously, 3 limits were added as a constraint, M=6, M=7 and M=8, which are values considered to be within a safe range in terms of continuous hours working. Similar analysis as the previous were made in order to determine the performance of the approach.

On the three threshold values of M, overall, the algorithm was able to reduce the number number of pump switches as the limits got lower, while maintaining the average number of hours working continuously per pump lower than the. However, on lower limits the tendency tends to be different, after breaching the limits N and M, some pumps tend to compensate the others, and in order to keep the number of penalties low while fulfilling the demand, the tendency is to increase the number of pump switches or the number of hours working consecutively. The results obtained can be seen on table IV. In this analysis we have chosen to show only the results that comply with tank limits imposed. Just like in the previous approach we have decided to show penalized solutions when it comes to the limits M and N, as this have proven to, as the limits get smaller, enhance the overall performance of the system. We can also highlight that this approach found a great number of penalised solutions when it comes to the tank level for both scenarios, meaning that the algorithm is struggle into converging to non-penalized search spaces. However, on this approach the ES was able to produce some great results. With a limit of M=7 and N=6, the algorithm is able to produce a cost of 247.15 for the cost driven scenario and 296.45 for the tank level scenario. Although the wear and tear of pumps shows similar conditions to the preliminary results, the fact that it produces a leveled tank driven scenario lower than the GA and the baseline, proves that under the right conditions, this algorithm can produce great results.

VI. Conclusion

After assessing the results we can conclude that the ES was successfully implemented.

When it comes to the performance of the algorithm this is a very computationally heavy algorithm showing long running times, portraying a very slow convergence and a tendency to be trapped on local optima solutions as at times it struggles to find non penalized solutions. Proving that the ES might not be the best option for such complex problems.

When it comes to its results, we can conclude that the algorithm is able to find good solutions when it comes to the cost of the WSS energy consumption. However, more often than not it fails to provide non-penalized results, proving to be very inconsistent on its convergence. The results obtained show that on a wear and tear perspective, the algorithm is sometimes able to find solutions that have less hours running over the thresholds and less number of pump switches, but usually those solutions show costs too high be considered. The fact that the results are so inconsistent means that this is not the right approach for this types of problems, as heuristics tend to find the near optimal solution and can be trapped on local search spaces. The fact that the best result was only found with both limits N and M applied means that it is highly reliant on the inputs used.

Another important conclusion, is that the fact that by using two different scenarios, both cost driven and tank level driven, shows great adaptability for the results, as it improves the robustness of this approach. Another characteristic that improves the flexibility of this model is the fact that the limits N and M can be change to accommodate different values.

Overall we can conclude that the case study of AdA can be further improved and the ES at the right circumstances can achieve that, but it shows great limitations that need to be improved in order for this algorithm to be more consistent and produce more reliable results that can help explore this problem.

VII. Recommendations

After accessing the performance the overall conclusion of this thesis, it is important to highlight some recommendations.

As the results provided show, there is a great inconsistency on the solutions calculated by the algorithm. To change this various techniques could be applied. Firstly, the parameters used on the evolution strategy can be different, using different rates. Secondly, to enhance the convergence of the model, some strategies, such as knowledge based individuals could be added to the initial population, guaranteeing that there are non-penalized solutions from the beginning. In order to deviate from tank level limit violated solutions a different penalty strategy could be used. When it comes to the pump switch constraint and the maximum number of hours working consecutively constraint, they could be added as weighted constraints, ensuring that when surpassing the limits, the values don not get too high. Afterwards, different values of the limit M can be applied, to simulated different conditions. To reduce computational effort different stop criteria can be applied, as well as an overall optimization of the code, as the code was developed to run this case study and could use further enhancement. Finally, in order to study further the cost versus maintenance trade-off this type of studies should be paired with a maintenance cost analysis throughout a vast time period in order to study the real life maintenance costs instead of using surrogate methods, as it would approximate the results a real life scenario.

	Minimum cost scenario cost (€)	Tank level Scenario cost (€)	Minimum cost scenario only with tank level constraint (€)	Tank level scenario cost only with tank level constraint (€)	Minimum cost scenario energy consumption (kwh/day)	Tank water level scenario energy consumption (kwh/day)	Minimum cost Scenario Number of switches	Tank Water level Scenario Number of switches	Minimum Cost average number of hours working consecutively (h)	Tank Water scenario average number of hours working consecutively (h)	Water tank limit violation cost scenario	Water tank limit violation level scenario
Preliminary	246.61	693.69	246.61	693.69	4859.57	5959.64	59	65	3.5	4.67	No	Yes
N=7	247.38	683.37	247.38	683.37	4889.83	5891.22	55	66	3.75	4.5	No	Yes
N=6	634.34	689.79	534.34	689.79	4872.91	5731.92	55	59	3.5	4.75	Yes	Yes
N=5	487.58	495.83	487.58	495.83	5713.01	5559.1	55	55	4.5	4.58	No	No
N=4	1454.29	1801.33	454.29	801.33	4898.38	5942.01	49	49	4.42	5.91	No	No
N=3	2013.67	2072.94	1013.67	1072.94	5054.45	5832.91	40	39	4.91	6.83	Yes	Yes
N=2	1679.83	1726.41	679..83	726.41	5794.88	5794.88	29	28	7.08	7.25	Yes	No
N=1	4491.72	4698.17	491.72	698.17	5603.72	5664.72	31	30	7.75	7.91	No	No

TABLE III: Penalty constraint results

	Minimum cost scenario cost (€)	Tank level Scenario cost (€)	Minimum cost scenario only with tank level constraint (€)	Tank level scenario cost only with tank level constraint (€)	Minimum cost scenario energy consumption (kwh/day)	Tank water level scenario energy consumption (kwh/day)	Minimum cost Scenario Number of switches	Tank Water level Scenario Number of switches	Minimum Cost average number of hours working consecutively (h)	Tank Water scenario average number of hours working consecutively (h)	Water tank limit violation cost scenario	Water tank limit violation level scenario
Preliminary	246.61	693.69	246.61	693.69	4859.57	5959.64	59	65	3.5	4.67	No	Yes
M=8, N=7	441.19	1210.19	441.19	1210.19	4834.65	5793.82	63	63	3.25	4	Yes	No
M=8, N=4	279.92	490.92	279.92	490.92	5515.38	5743.88	45	45	5	5.08	No	No
M=8, N=3	1460.92	1503.8	460.92	503.8	5066.68	5889.46	38	38	4.91	5.33	No	No
M=8, N=1	9484.78	9687.87	1484.78	1687.87	5679.12	5741.12	48	47	5.41	5.42	No	No
M=7, N=7	285.09	490.67	285.09	490.67	5593.59	5707.24	70	70	3.67	3.75	No	No
M=7, N=6	247.15	296.05	247.15	296.05	4853.90	5797.81	60	64	3.25	3.75	No	No
M=7, N=4	1691.23	1703.80	691.23	703.80	5645.17	5860.01	50	49	4.5	4.75	No	No
M=7, N=2	6461.82	7298.47	461.82	1298.47	5030.57	5710.68	35	35	4.66	6.59	No	No
M=7, N=1	10343.28	10595.67	343.28	595.67	4929,41	5726.49	49	52	4.58	5	No	No
M=6, N=7	1055.91	360.86	1055.91	360.86	4998.09	5824.82	70	70	3.5	3.75	No	Yes
M=6, N=5	703.94	628.93	703.94	628.93	4904.20	5675.98	53	54	3.92	3.75	Yes	No
M=6, N=4	488.68	1361.72	488.68	1361.72	5635.98	5786.08	50	49	4.08	4.17	No	No
M=6, N=2	7453,24	8502.49	453,24	502.49	4938.73	5781.73	35	35	4.62	5.25	No	No
M=6, N=1	8453.24	8772.85	453.24	772.85	4923.27	5712.31	49	52	4.5	5.16	No	No

TABLE IV: Penalty constraint results

References

Al-Ani, D. & Habibi, S. (2012), Optimal pump operation for water distribution systems using a new multi-agent particle swarm optimization technique with epanet, *in* '2012 25th IEEE Canadian Conference on Electrical and Computer Engineering (CCECE)', IEEE, pp. 1–6.

Alperovits, E. & Shamir, U. (1977), 'Design of optimal water distribution systems', *Water resources research* **13**(6), 885–900.

Alvisi, S., Franchini, M. et al. (2016), 'A methodology for pumping control based on time variable trigger levels', *Procedia engineering* **162**, 365–372.

Amádis Santos, Fernando Oliveira, G. S. J. C. L. L. M. V. P. C. P. N. P. C. e. P. Q. (2018), *Guias técnicos-USO EFICIENTE DE ENERGIA NOS SERVIÇOS DE ÁGUA*, Entidade Reguladora dos Serviços de Águas e Resíduos.

Cheung, P. B., Reis, L. F., Formiga, K. T., Chaudhry, F. H. & Ticona, W. G. (2003), Multiobjective evolutionary algorithms applied to the rehabilitation of a water distribution system: A comparative study, *in* 'International Conference on Evolutionary Multi-Criterion Optimization', Springer, pp. 662–676.

Dai, P. D. & Li, P. (2015), Optimization of pumping energy and maintenance costs in water supply systems, *in* 'Modelling, Computation and Optimization in Information Systems and Management Sciences', Springer, pp. 93–104.

De Paola, F., Fontana, N., Giugni, M., Marini, G. & Pugliese, F. (2016), 'An application of the harmony-search multi-objective (hsmo) optimization algorithm for the solution of pump scheduling problem', *Procedia engineering* **162**, 494–502.

Farmani, R., Walters, G. & Savic, D. (2006), 'Evolutionary multi-objective optimization of the design and operation of water distribution network: total cost vs. reliability vs. water quality', *Journal of Hydroinformatics* **8**(3), 165–179.

Feldman, M. (2009), Aspects of energy efficiency in water supply systems, *in* 'Proceedings of the 5th IWA water loss reduction specialist conference, South Africa', pp. 85–89.

Kazantzis, M., Simpson, A., Kwong, D. & Tan, S. (2002), A new methodology for optimizing the daily operations of a pumping plant, *in* 'Proceedings of the 2002 conference on water resources planning'.

Kirkpatrick, S., Gelatt, C. D. & Vecchi, M. P. (1983), 'Optimization by simulated annealing', *science* **220**(4598), 671–680.

Kougias, I., Katsifarakis, L. & Theodossiou, N. (2012), 'Medley multiobjective harmony search algorithm: Application on a water resources management problem', *European Water* **39**, 71–52.

López-Ibánez, M., Paquete, L. & Stützle, T. (2006), 'Hybrid population-based algorithms for the bi-objective quadratic assignment problem', *Journal of Mathematical Modelling and Algorithms* **5**(1), 111–137.

Luna, T., Ribau, J., Figueiredo, D. & Alves, R. (2019), 'Improving energy efficiency in water supply systems with pump scheduling optimization', *Journal of cleaner production* **213**, 342–356.

Mala-Jetmarova, H., Barton, A. & Bagirov, A. (2015), 'A history of water distribution systems and their optimisation', *Water Science and Technology: Water Supply* **15**(2), 224–235.

Su, Y.-C., Mays, L. W., Duan, N. & Lansey, K. E. (1987), 'Reliability-based optimization model for water distribution systems', *Journal of Hydraulic Engineering* **113**(12), 1539–1556.

Vieira, F. & Ramos, H. (2008), 'Hybrid solution and pump-storage optimization in water supply system efficiency: A case study', *Energy Policy* **36**(11), 4142–4148.

Wu, Z. Y., Boulos, P. F., Orr, C. H. & Ro, J. J. (2001), 'Using genetic algorithms to rehabilitate distribution systems', *Journal-American Water Works Association* **93**(11), 74–85.

Xevi, E. & Khan, S. (2005), 'A multi-objective optimisation approach to water management', *Journal of environmental management* **77**(4), 269–277.