Multi-objective optimization tool for PATs operation in water pressurized systems

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Abstract

The use of pump working as turbine (PAT) instead of the traditional pressure regulation systems could allow for a recovery of the excess hydraulic energy to reduce the energy footprint of the water supply industry and at the same time control the water losses by an effective reduction in pressure induced by the turbine head drop. This research aims to explore the option of applying multiple recovery systems in a water network with an integrated multi-objective optimization using genetic algorithms. The objective of the optimization is to ensure a better use and effectiveness in the implementation of these solutions. A methodology to approach this multi-objective solution and the interface between components of the optimization is developed and presented. The evolutionary capacities of the optimization is analysed and the effects of the general convergence of the Pareto surface front with the adaptation of the final solutions to the available PATs.

Keywords: pump-as-turbines (PATs), genetic algorithm (GA), multi-objective optimization, water losses, micro-hydro production, water-energy nexus

1 Introduction

Micro-hydro can be a valuable answer to the need for low-cost and long-life electrical energy production, using natural or artificial waterfalls, which do not harm the environment. Unconventional solutions are at the forefront of many developing countries to achieve energy self-sufficiency (Ramos and Borga 1999). The reduction of the water leakages should be considered as a new chalengue using the recovery systems (Giustolisi, Savic, and Kapelan 2008). Water distribution networks are low-energy efficiency systems since they need high energy levels to satisfy consumption in terms of available pressure, increasing the water leakage volume, the consumed energy by the system and the decrease of the sustainability indexes (Morani et al. 2020).

A major consequence of climate change is the drastic change in weather patterns and the rise in global temperatures. Therefore, it creates more stress on the already scarce natural water resources. Multiple regions, especially in Europe in the Mediterranean latitudes, are already suffering from water scarcity, some even already produce artificial water with the use of desalination methods which is a very expensive and energy-dependent process (2.5kW/h/m^3) that goes against the motivation of reducing and managing the natural resources (Bartels and Andes 2013). The worldwide excess of pressure in the water supply systems, and their level of deterioration, create an estimated average water loss of around 35%, being possible in extreme pressure regions and very deteriorated systems this level can reach up 60% (Kizilöz and Şişman 2021).

There is a direct correlation between excessive pressure and water losses due to leakage in a network. Therefore, good pressure management is essential to regulate water losses (Parra and Krause 2017). The excess pressure, which is recovered by the machines can be transformed into energy and consequently, it gets an efficiency improvement of the system using renewable energies (Moazeni, Khazaei, and Pera Mendes 2020). PATs is one of them and its analysis was considered by modeling the system. The use of PATs has been thoroughly studied, from the prediction of the behaviour of the turbomachine in inverse mode by analytical methods to the use of Computer Fluid Dynamics (CFDs) (Binama et al. 2017). The location and definition of an energy recovery system that uses PATs as the main elements are an extremely complex problem to solve, although some research were published to search for the best solution when there are multiple variables (Tapia, Reina, and Millán 2020). Different researchers have shown the feasibility of these micro-hydro systems to get an advantage from the excess pressure in a water system (Novara et al. 2019). These machines operate in reverse mode and they proposed an unconventional solution to reduce the pressure (Ramos and Borga 1999). Due to the reduced investment, corrective interventions, better customer service by the water supply companies and savings in energy necessary to pump or treat the water, this type of water losses management can be one of the most economical key (Girard and Stewart 2007). Different analytical methods were proposed based on deep experimental campaigns (Novara et al. 2019), which enabled the development of operational curves estimation (head, efficiency and power) when the machines operate under variable rotational speeds (Ávila et al. 2021). When the optimization procedure is analyzed, different published researches considered the challenge. A new mixed integer non-linear model was developed to locate PAT and pressure reduction valves (PRV) in water systems (Morani et al. 2021). (Fernández García and Mc Nabola 2020) proposed a methodology that was focused on the detection of the optimal location and number of PATs to maximize hydropower generation in gravity water distribution networks. It used a nonlinear programming based on sequential addition of devices. In this line, a method based on a highly parallelized evolutionary algorithm, employing a hydraulic solver to evaluate hydraulic constraints (Tricarico et al. 2018). A case study was shown, applying a bi-objective optimization for the installation of PATs. It showed solutions able to recover hydropower up to 83 kW in Catania, Italy (Creaco et al. 2020). Previous case studies show the search of solutions for the improvement of the energy efficiency in the water systems using genetic algorithms (GA).

Genetic Algorithms (GAs) are a heuristic search method, which is highly used in the resolution of problems in different scientific domains (Baños et al. 2011). GAs are based on the dynamic system that makes the theory of evolution in the natural world. They consist in the survival of the fittest solution and its development to become even better adapted, with the possibility of surpassing the original fittest solution, becoming itself the fittest (Goldberg 1989). (Baños et al. 2011) developed a deep review of different computational optimization methods, which can be used when renewable systems (e.g., solar, wind, hydro, among others) want to be applied. Different meta-heuristics methods were used last years. Some of them are: (i) Pareto envelope-based selection algorithm (PESA/PESA-II) (Corne, Knowles, and Oates 2000); (ii) Population-based meta-heuristics which include the multi-objective tabu search (MOTS) (Baños et al. 2007); (iii) Pareto archived evolution strategy (PAES) (Knowles and Corne 2000); (iv) non-dominated sorting genetic algorithm (NSGA/NSGA-II) (Miriam, Saminathan, and Chakaravarthi 2020); (v) Pareto simulated annealing (PSA) (Czyzç and Jaszkiewicz 1998); (vi) metamodeling-based simulation optimization (MBSO) (Soares do Amaral et al. 2022) as well as other combinations of previous methods, such as multi-objective simulated annealing and tabu search (MOSATS) (Alcayde et al. 2010).

In line with this research, there were multiple studies and progresses in the use of genetic algorithms in a multi-objective problem (Liu and Rodriguez 2021). The analysis of sizing networks was developed by (Palod, Prasad, and Khare 2021), pump systems (Piri et al. 2021), demand analysis (Bouach and Benmamar 2021), pressure reduction valves to reduce leakage by the reduction of pressure in the water system (Bouach and Benmamar 2021). The solution to this problem is usually approached by creating a fitness function that evaluates simultaneously multiple criteria to improve the solution, especially in multi-variable problems when it does not know the correct relative importance of every objective (Katoch, Chauhan, and Kumar 2020), in which the Pareto solution is a good tool to choose the optimum and non-dominated solution, being introduced by (Chankong, V., & Haimes 1983).

The purpose of this research is to study the effects of the application of a GA in a multi-variable approach to the implementation of an energy recovery system, with the use of PATs. The goal is to apply all the variables in one compact genetic procedure. The variables used are power curves and characteristic curves for multiple rotational speeds, implicating the use of electric regulation of the system conditions, and different demand patterns, throughout the day. Although this work is focused on the application of a system in the short term, it opens the way to a long-term approach that could include as a variable the progression of the demand pattern throughout the life cycle of each system. The developed optimization is based on the NSGA-II (Deb et al. 2002) and it was applied using a MATLAB programming language in the correspondent computer software (Chapman 2015). It is intended to evaluate the use of the EPANET-MATLAB Toolkit in this kind of optimization (Lewis A. Rossman 1999). This toolkit creates an interface between both software, enabling the analysis from the hydraulic simulations in the EPANET model. As novel, the research applied the optimization procedure using modified affinity laws (Plua et al. 2021) and it was applied in a supply network in Lisbon (Portugal).

2 Methodology

The proposed optimization procedure is divided into six different stages, in which each one contains different steps. The methodology is based on routines specifically developed and presented in this study. It is important to note that every major variable that impacts the system performance in the short term was incorporated in this optimization process. Meaning that the GA must deal with a complete simulation that takes into consideration not only a demand pattern but also a multitude of options in the PAT library. With this procedure, a higher range of possible solutions exists and the difficulty to achieve good solutions is also inherently higher. As previously described, the goal is to analyse an entire network and its characteristics in a robust system. The methodology is comprised of six steps (Figure 1) as follows:

Step I is focused on the use of the input data and the establishment of the optimization setup. The inputs required at the beginning of the optimization cycle dictate the evolution of the system and at some level part of the system constraints. The elements that include the input data are as follow crossover ratio, mutation ratio, population size, the total number of generations, percentage of high-pressure tolerable region, reference of ideal pressure, the position of high pressure and the probability of not applying a PAT.

Step II is dedicated to developing the initial random population to start the development of the hydraulic simulation.

Step III is focused on the hydraulic simulation and network edition. As stated, the procedure bottleneck is the interface between the optimization procedure in MATLAB and the hydraulic simulation of the water network in EPANET. Two main components in the process should be noted: (i) the genetic optimization algorithm, and (ii) the hydraulic network edition and simulation (Figure 2). For an efficient interaction between the two simulation tools, the network morphology of each solution was comprised of one common matrix (Figure 2). The implementation of GPV valves from EPANET and their characteristics curves are the most critical step in this process because it is repeated multiple times (time steps . the number of valves per generation . the number of generations) along with every time step and PAT (in the general propose valve - GPV). Each link is evaluated for each PAT installation. The correspondent characteristics are implemented for the given time step. The results are contained in a similar matrix format as the population one (Figure 2).

By having every element of the population encompassed in one matrix with a simple nomination of the characteristics, such as the binary or index connotation of the features to be stated in the network, not only it becomes easy to process the hydraulic network but allows for compatibility with simple evolution methods of mutation and crossover. Each level, in the (z) axis of the matrix, corresponds to a chromosome of each solution, meaning that the size of the matrix in this dimension depends on the number of elements in the initial population decided by the user. Inside of each (z) plane, there is a line in the (y) axis for each link of the network and every column, in the (x) axis, is responsible for a characteristic related to the possible PAT installed in the link (Figure 2). A PAT is then installed (On/Off) with the correspondent model of system regulation of hydraulic (HR) type, electric regulation for different rotational speeds (ER), hydraulic and electric regulation (HER) simultaneously modes (Carravetta, Derakhshan, and Ramos 2018) or using different PATs installed in a single-serial-parallel (SSP) regulation types (Carravetta, Fecarotta, and Ramos 2018) (Figure 3) .

Step IV is dedicated to the GA procedure. To select the best individuals in the solution space created by the genetic algorithm (GA) and the hydraulic simulation, a competition amid objectives must take place. The main objectives, which should be achieved from the installation of a PAT in a water distribution network and utilized in this study are: (i) the regulation of pressure in the network, (ii) the production of electricity and (iii) the feasibility of the system.

Hence, for this methodology an optimization algorithm is used as represented in Figure 2.

An initial approach to the pressure regulation function was made with an extrapolation of the methods used in multi-objective optimization of water networks with the implementation of Pressure Reducing Valves (PRV), where the pressure function used was based on (Araujo, Ramos, and Coelho 2006)

$$Pressure\ funtion\ fitness \rightarrow PFF = [\tfrac{1}{2}\textstyle\sum_{j=1}^{n}(h_j - h_{ref})^2]^{1/2} \quad (1)$$

where, h_j is the pressure at node (j) in a given time, n in the number of nodes in the networks and h_{ref} is the reference pressure assigned for the network. In the approach used in this research, the convergence only can occur from the high-pressure region to the low-pressure, not allowing for convergence from both sides of the spectrum, and the low-pressure solutions are considered immediately out of bounds and they do not have a reproductive chance.

The second fitness function is stated on the feasibility, analysing the cost-payback period. The energy production from PAT should not be viewed only as an alternative to PRVs since it has the possibility to generate some extra income over the years. A cost per kW of energy produced was calculated for the fitness function. The cost function come from a compilation of different values associated with 301 radial and 42 vertical multistage PATs (Novara et al. 2019). It was realized the function of the cost was broken into two regions:

(i) from 0kW to 1kW;

$$Cost\ funtion\ fitness \rightarrow CFF1\ \left(\frac{€}{kW}\right) = -17512P^3 + 38193P^2 - 28846P + 9448{,}3 \qquad (2)$$

(ii) for > 1kW.

$$Cost\ funtion\ fitness \rightarrow CFF2\ \left(\frac{€}{kW}\right) = 1498{,}4P^{-0.686} \qquad (3)$$

where P is the generated power in kW.

The last fitness function measures the accumulated electric power produced in the network. To recover the hydraulic power in each PAT, the fitness function uses the power curve data that was already incorporated in the GA library. After locating the correct curves of the PAT model and rotational speed for a given time step, the fitness function defines the generated power by interpolating the PAT flow that came from the hydraulic simulation with the values on the power curve. The function fitness is defined by the following expression:

$$Power\ funtion\ fitness \rightarrow EFF\ (kW) = \gamma Q H \eta \qquad (4)$$

where γ is the specific weight of the fluid in (kN/m^3); Q is the flow in m^3/s; H is the recovered head in m w.c.; and η is the global efficiency of the machine.

As previously stated in the methodology, crossover and mutation are both critical elements in GA optimization. Both depend on a user input that defines them respectively by the Crossover and the Mutation ratios. The ratios are the equivalent probability of a certain characteristic in the chromosome of the solution to be modified when under the evolutionary processes to find a better-suited individual. During the Crossover operations, the respective ratio was used to define the actual solutions that should take part in the exchange of genetic material to create two new chromosomes. In the mutation operator, the ratio was used freely. Meaning that a random number is associated, coordinate wise, to every gene in every chromosome of the solutions to adapt. If it was inside the range of probability defined by the ratio a mutation would occur. The mutation operator intervenes only after the crossover operator.

The effects of different ratios in the evolutionary operators is the topic of multiple studies (Hong, Wang, and Chen 2000). The different methods used to apply both evolutionary operators and the corresponding ratios can change the results and the convergence of the optimization. Usually, with the use of static ratios, meaning that remains the same during the whole duration of the optimization, the values of the mutation probability are very low when compared with the crossover probability. Mutation exists mainly, not entirely, to guarantee the discovery of new regions of the solution space and crossover to optimise the individual solution in each local maximum.

At the start of any GA, there must exist an initial population that is randomly generated (Step II). In many cases (e.g. as in the case of optimization function) it does not require special attention to the randomly generated variables. In this case, there is a physical implementation of a turbine, and it could be relevant to change the initial concentration of PAT, from the analysis perspective. A variable defined as δ was included in the input data and defines the probability of not having an installed PAT at a given link. In the creation of the new population if the randomly created variable exceeds δ, then a PAT is considered active in that link. The population size and the total number of generations are also defined. The correlation between these two parameters is also difficult to correctly determine. The traditional approach is to maintain a constant population, but studies have concluded that for small searching spaces a small population is more effective, being the opposite true to find solutions in large search areas (Rajakumar and George 2013). The approach used in this research was to maintain the traditional constant population (Abdelaziz 2017).

In Step V the definition of the Pareto solution is done. The space of solutions to be analysed comes from a non-continuous function. A GA approach to a continuous function, where the changes in inputs can be smooth, offering a constant and gradual progression of results. In this kind of approach to non-continuous solution space, the resulting convergence is predicted to behave in a breakthrough-to-breakthrough evolution. The true Pareto front is not made of continuous points, and each Pareto solution may be very distinct from each other not only in terms of the fitness function output but also in the true characteristics of the chromosomes. A geometrically imperfect surface Pareto front is thereby expected in this multivariable non-continuous solution space. This means that when observing the Pareto front in a graphical representation it seems there would exist missing solutions in a certain region due to the distance between results. There is the possibility that the Pareto front with those apparent defects is a good approximation due to the discontinuity of values. The procedure considered different strategies to apply penalization constraints for the different functions. When PF was analysed, the penal was applied by multiplying the difference between desired pressure and the actual pressure to the square, the result provides an automatic valorisation of smaller errors and a natural penalization of nodes that have very high pressure. CF considered the operation limits of the cost functions and the energy production considered the difference between rotational speed (n) and the nominal rotational speed (n_0).

The final stage (Step VI) is focused on the adaptation and simulation of the water system using the best solution obtained by GA.

3 Result and discussion

3.1 Case study

The analysed case study corresponds to one of the sectors of Funchal (Portugal) (Figure 4a) water network to reduce the number of pipes and to be possible to adapt the circulating flows to the available database of PATs. Hence this sector was divided into three different district metered areas (DMAs) being the minimum pressure in the consumption nodes equal to 30 m w.c. (Figure 4b). The restriction pressure was 15 m w.c. when non-consumption nodes were analysed. The consumption pattern, which was assigned to the base demand in each consumption node was shown in Figure 4c. The extended analysed period was 24 hours and it was simulated by using EPANET (L. A Rossman 2000). The hydraulic simulation (Step III of the methodology presented in Figure 4) considered the different PAT curves using the general propose valves (GPV) to analyse the recovered head and flow over time, and therefore, to develop the estimation of the generated energy. The proposed layout was considered an electro-hydraulic regulation using a parallel pressure reduction valve (Fontana et al. 2021), which operates when the machine is not able to recover energy due to the rotational speed being out of its operating range. The penalization was in the multiplication of the pressure fitness function result by a penalization constant. This constant was considered 100 in this study. It was applied for excess nodes with high pressure above the maximum value in the water system.

The characteristic curves and the corresponding used PATs were from the pumps manufactured by KSB. The curves are already provided for the pump-as-turbine mode. A library of seven different real PATs was used as a variable for the system optimization. The different characteristic curves at the nominal rotation speed (n_0 = 1520 rpm) are shown in Figure 5. The combination of the chosen PATs was made to ensure an evenly spread operation zone. To achieve it, selected pumps both with high head and low demand, and vice versa were chosen. For each point in each PAT, the turbomachine affinity laws were applied, defining the H-Q characteristic curves and providing the behaviour on the best operating point. Also, the power curve was calculated, in the same way, using the affinity laws of turbomachines. The operation range was defined between $0.5n_0$ and $1.5n_0$ when the modified affinity laws were applied in this analysis (Plua et al. 2021).

3.2 Optimization results

The general methodology of the routines defined in the previous section was codified considering the complete simulation, such as demand patterns and a multitude of options in the PAT library. The simulations were made with an AMD Ryzen 7 3750H (2.3Ghz) CPU where only one core was dedicated to the processing. Taking into account the number of solution permutations possible with the chromosome/solution matrix, the multiple PATs and operating conditions available and the time steps, the total number of possible solutions is $4{,}12 \times 10^{56}$. During the optimization, the Pareto front results for each generation and their conversion was registered and presented in the MATLAB interface as shown in Figure 6.

Figures from 7a to 7c only show better results at the respective selected generation. Solutions that remained dominant for multiple generations create a line made from constant points of the same pressure fitness. When a solution is no longer present in the next generation in the graph, it means it was surpassed by another solution created with the evolutionary operators. Figure 6a shows the generated power (kW) for each Pareto front solution in a certain generation. The fitness function results that represent the cost per power unit of each solution (C/kW) and the pressure fitness (PF) results are shown in Figures 7b and 7c respectively. Figure 6d shows the 3D current surface Pareto front updated for each generation of the GA. It enables an easy interpretation of possible relations between solutions and fitness functions.

A rapid convergence took place in the initial generations of the optimization according to (Korejo et al. 2013). This fast convergence is justified by the high initial variability of the solution which forces better results provided by the intersection of this genetic material with the use of the crossover operator. Simultaneously, a hard approach to the limits of the search space can also influence this original convergence. The tolerance for the low pressure in the nodes would be null, meaning that in the initial population the majority of the solutions did not show a competitive ranking since it was considered to be out of bounds. Therefore, the reproduction operator ended with few solutions, having those solutions more probability to produce offspring. The increase of mutation chances and crossover in the children's pool adding to the already high probability of an alteration to the solution to create a better one, since very few good solutions had already been discovered that can provide a competitive dominance. When the electrical regulation was considered, the first interactions had also very small adaptability, only later in the phase were the solutions in the Pareto front became more stable the regulation of the appropriate rotational speed for each PAT and each hour of the day started to have a permanent effect. Before this phase, a regulation in rotational speed can be very quickly surpassed by substitution in the PAT model or simply the domination of other solutions.

A clear relation that can be previously expected is that with higher power generation the lower the fitness pressure is. It is a straightforward condition, that although simple, is a testimony of the correct behaviour of the optimization algorithm. The reduction of pressure is equivalent to the reduction of potential energy in the water network. When the excess potential energy is reduced using PAT, even in a scenario that the PATs would be working in undesirable efficiency conditions, the recovered energy recovered would tend to increase in the system, therefore improving the optimization procedure.

The pressure fitness function was used as a reference to evaluate the convergence of the optimization in this research because it is the only quantifiable fitness function since the true Pareto front was unknown. The arbitrary average difference of 10 m w.c. in every node was used as a reference for pressure management. Using these pressure values, a final value of pressure fitness was got to compare the results. Other reference values were also obtained considering 20 and 30 m w.c.. If the Pareto front achieves the region of no penalization, an artificial drop in the pressure fitness value would happen on the scale of 100 times inferior. In these reference values, the penalization is added to maintain the values on the same scale for comparison.

A refinement post-optimization of the PAT characteristics was evaluated for the solution with the best pressure fitness. The pressure profile for the refined solution for each given time step is represented in Figure 7. The GA optimization seeks the overall best set of solutions to the water network, therefore, in the final stretch of optimization where the mutation operator is more important, the duration of the convergence may be slower. Fast refinement of the already simplified solution after the optimization process can improve the results that may take multiple generations to improve with the GA. Table 1 details the speeds referent to the pressure profile of Figure 7. This refinement was based on the use of the modified affinity laws to fit better the values of efficiency since the optimization procedure used the affinity laws. The best estimation of the efficiency curves enabled the improvement of the estimation of the recovered values compared to affinity laws, which considered the maximum value of the efficiency is constant for each value of rotational speed. This refinement was based on the equations published by (Plua et al. 2021).

The selected machines were KSB65-160 for the location of PAT1 and PAT3 and KSB 80-200 for PAT2. Table 1 shows the different values of flow, head, efficiency and ratio of the rotational speed over time. At each time, the optimization procedure considered the variation of the rotational speed applying the modified affinity laws (Plua et al. 2021).

The theoretical analysis enabled the definition of an operative rotational speed to maximize the recovered energy according to the range of flow and considering the runaway curve. PAT1 was inactive seven hours between 0 and 7 am due to the low flow values of the night. The maximum generated power of PAT1 was 1.61 kW and the daily recovered value was 16.83 kWh. The rotational speed changed between 0.5 and 1.02 and its efficiency oscillated between 0.66 and 0.72 as a function of the flow over time. When PAT2 was analysed, the maximum generated power was 3.91 kW and the average daily recovered energy was 39.29 kWh. PAT2 changed the rotational speed between 0.5 and 0.87 compared to the nominal rotational speed and the efficiency was between 0.73 and 0.78. PAT3 operated between 0.50 and $0.57n_0$ and its efficiency oscillated between 0.6 and 0.64. The maximum recovered power was 0.5 and the daily recovered energy was 2.81 kW. When the average energy values were extrapolated over a year, the annual recovered energy was 21507 kWh. When the PATs were not active, the installed parallel pressure reduction valve worked in other to dissipate the excess of energy. The dissipated head is indicated in Table 1, since this head is equal to the recovered head value of the PAT when the rotational speed is lower than $0.5n_0$.

4 Conclusions

The use of an integral approach, as the one used in this research, to optimize solutions with PATs as the base element in a multi-objective problem shows a feasible option that could allow for efficient optimization of large water networks. The fitness functions and restrict constraints showed a good convergence of the solutions, having nevertheless room for improvement by allowing solutions that are in the negative pressure region to improve the variability of the solutions in the Pareto front and possibly the speed of convergence. The proposed methodology of combining all the information in the proposed population matrix proved to be a robust option.

The use of all fitness functions developed for this research showed an effective comparison between solutions and allowed for a competitive evolution of the Pareto front. The velocity of convergence diminished during the simulation. The lack of reproductive ability of the solutions due to the size of the population or the achievement of a very optimized surface Pareto front by the GA could be a cause for this observation. The optimization results demonstrate a clear improvement in the pressure conditions. Besides offering adequate solutions that respect the limits of what is the acceptable solution space, it offers a direct improvement after the optimization to 78% of the original pressure. After refining the rotational velocities in the solution, pressure levels of 59% of the original pressure were achieved. With the use of PATs better adapted to the conditions present in the water network, it is possible to achieve even better results.

The methodology, which was developed in this research showed the effectiveness in the convergence of the Pareto front and its adaptation using the evolutionary operators. The use of EPANET-MATLAB Toolkit, despite being a good solution to analyse data from water networks using powerful mathematical software like MATLAB, is not adequate in performance capabilities to the number of network editions and simulations needed to have results closer to adequate populations and generations in the optimization.

The inherent probability associated with this optimization method to act and generate a better solution for a faster convergence creates the question of whether an adaptive mutation and crossover ratios could have an impact on the convergence of the resulting Pareto front. By using adaptive mutations ratios, either a predefined transformation according to the number of generations or the continuous adaptation to the modifications in the Pareto front, it was created an incentive by improving the mutation ratio when the Pareto front starts to stabilize. Hence, the variability is forced to be induced in the Pareto front and accelerated either the discovery of new regions in the solutions space, as to improve the tuning of the electrical regulation definitions for each time step.

An approach to these results with a standard penalization, when it is applied for the case of a too big high-pressure region may not be enough, since it may offer too much equality between solutions. In one case the solutions are viable, and in the other where there are small pressures in the pipe system, networks are not physically possible or adequate to the supply enough water.

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