Minimizing the head losses increases caused by valves in hydraulic networks

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Abstract

This paper presents a hybrid model that calculates the heads, the discharges in pipes, the head losses in pipes (caused by discharges and valves) and the booster heads in hydraulic networks. The steady state is calculated considering the hydraulic network without valves and boosters. The extended period simulation is calculated considering the presence of valves and/or boosters to solve over pressure and/or under pressure problems respectively. The hybrid model uses a genetic algorithm to minimize the dissipated hydraulic power sum in the whole hydraulic network for all calculation time steps of the extended period simulation (objective function) by setting optimal valve openings. It was studied how it affects the behavior of a hydraulic network. A real hydraulic network that had over pressure and under pressure problems was analyzed. It was necessary to install boosters and valves to solve the pressure problems. The results show that when valves were installed without planning its openings, the total head losses increased from 5.9% to 13.6%, while the total head losses in the same hydraulic network increased 2.7% when planning the installed valves openings. It's concluded that the dissipated power minimization was an effective way to optimize the studied hydraulic network operations by minimizing the head losses increases caused by the installed valves.
Keywords: hydraulic networks, valve openings settings, dissipated power, optimization.

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1 Introduction

In the field of water resources, the imbalance between supply and demand requires solutions more and more efficient. As countries develop, problems related to water, like cities supply, water transference among watersheds and mainly the lack and the difficulty to obtain financing founds to build new hydraulic works, demand the existing systems to be more and more efficient (Diniz *et al.* [1]).

The operational control of hydraulic networks to attend the demands of the population throughout the day is a problem that has been researched for many years and until nowadays the solutions are not always optimized, resulting in risks of failure in water supply (Diniz *et al.* [1]).

Over time, several techniques have been developed to choose the optimum alternative and the most well-known are: the linear programming, the non-linear programming, dynamic programming, the simulation and the use of evolutionary algorithms, like the genetic algorithm. The first three don't have many applications in real cases of engineering, but are sufficient to ensure viability. The simulation is the most used technique in practice and provides means for the detailed treatment of the systems behavior, although it's not optimizing. Genetic algorithms adapt concepts of genetics and evolution to generate a process of optimization in hydraulic networks operations and other fields of study (Diniz *et al.* [1]).

Several authors have been applying a lot of optimization techniques in the development of global design algorithms. In general, the objective of most optimization techniques is always the minimization of costs and until nowadays, this tendency remains. Despite the large number of algorithms that have been developed, none of them has been fully accepted or has been widely applied in the accomplishment of hydraulic network designs and operations. This is due, in part, to the great complexity of the techniques required to optimize the solutions (Diniz *et al.* [1]).

In this work, instead of using an objective function to minimize any given cost, it was decided to use a genetic algorithm to minimize the dissipated hydraulic power sum in the whole hydraulic network for all calculation time steps of the extended period simulation (objective function) by setting optimal valve openings and study how it affects the behavior of a real hydraulic network.

2 Literature review

Bureerat and Sriworamas [2] proposed a numerical technique called a network repairing technique (NRT). It is proposed to overcome difficulties in operating multiobjective evolutionary algorithms (MOEAs) for network topological design. It was also developed two new MOEAs to tackle the design problems: multiobjective real code population-based incremental learning (RPBIL) and a hybrid algorithm of RPBIL with differential evolution (RPBIL–DE). It was concluded that NRT is an efficient numerical scheme for dealing with an illegitimate pipe network topology in the conceptual design of water distribution networks (WDNs). From the numerical experiment, it was also concluded that

NRT can be applied for simultaneous topology and sizing optimization of water distribution networks efficiently and effectively. With the use of NRT, any multiobjective evolutionary algorithm can be employed to solve pipe network topological optimization. For the proposed hybrid RPBIL–DE for solving simultaneous topology and sizing optimization of pipe networks, it is shown that the algorithm is among the top performer MOEAs according to the hypervolume indicator. The method gives the best convergence rate for the cases of design problems with lower number of design variables. With the use of the proposed optimization strategy, a set of Pareto optimal solutions can be obtained and a designer can apply decision making techniques to select an appropriate network solution. The selected network can then be refined in the detailed design stage. In fact, NRT is also challenging if one can perform the conceptual, preliminary and detailed design (such as valve locations and distribution) at the same time, which means one can have a ready to work network within one optimization run.

Creaco and Pezzinga [3] presented a hybrid multiobjective algorithm for the combined optimization of pipes and control valves for leakage reduction in water distribution networks. The algorithm was initially applied to the optimal valve location problem, where it explores the trade-off between the number of installed control valves and the daily leakage volume. The applications proved the new algorithm is more effective than the multiobjective genetic algorithm widely adopted in the scientific literature. The main advantage of the new algorithm lies in the fact that it considers the presence of isolation valves in the network, which can be closed in order to contribute to leakage attenuation and to eliminate water paths around the control valves, thus facilitating control-valve regulation. Secondly, the algorithm performed simultaneously pipe replacements and control valve installations. In this case, a Pareto front of trade-off solutions between installation costs and daily leakage volume was obtained. For the choice of the final solution within the front, an economic criterion based on the long-term economic analysis was also presented.

Giustolisi *et al.* [4] investigated pumping optimization background leaks, that is, the nonrevenue water cost beside the energy cost. It was shown that the classical practice of filling the tanks during the night because of a lower level of demand and electricity tariff increases costs because of water loss from leaks. It's concluded that accounting for water losses beside energy cost results in the cost of nonrevenue water increased by night pumping, which might prevail over the general reduction of energy cost because of the hydraulic advantage of using the filled tank along the peak demand hours. It's also concluded that it would be better pump water along the day to fill tanks instead of pumping along the night and reduce the number of working pumps could be a better practice to control leaks beyond energy cost optimization.

Xiao *et al.* [5] developed a segment and outage segment generation technology to divide the entire system into multiple segments, which contains a portion of pipes and nodes. From the general statistics information of the segment, it was possible to find the optimal strategy of valve shutdown and assessing the reliability (defined as the ability of the network to provide adequate demands to consumers within specified limits of pressure) of a Chinese city hydraulic network. It's concluded that the analyzed hydraulic network had a low reliability and an optimization suggestion was proposed.

Haghighi and Asl [6] developed a package utilizing the fuzzy set theory, the method of Non Dominated Sorting Genetic Algorithm (NSGA-II) and the hydraulic simulation model of EPANET to take into account the uncertainty of pipe friction coefficients and nodal demands in the hydraulic analysis of water supply networks. In the proposed scheme, the notion of dominance in viewpoints of density and diversity of Pareto solutions was modified. A new metric named as the closeness–distance was substituted for the crowded-comparison operator in the standard NSGA-II. This new metric guides the Pareto solutions toward the extreme points on the Pareto fronts which are, in fact, the global optimum values of the objective functions. The model was applied to an example and to a relatively large pipe network. It's concluded that small uncertainties (estimation of pipe friction coefficients and nodal demands) in the network can result in large uncertainties in the hydraulic responses and significantly influence the system's performance reliability. The application of the NSGA-II makes the problem solution more systematic and computationally more efficient so that, many of the fuzzy hydraulic responses can be simultaneously analyzed in only one single simulation run.

Beygi *et al.* [7] considered two urban water distribution networks (WDN) optimization design problems having different objectives, including initial costs and hydraulic performance improvement of the network by satisfying given hydraulic constraints. The main objective was to simultaneously consider the utilities of both consumers and investors that are the main beneficiaries of such infrastructures. Initially, without any need to obtain input data from stakeholders, an acceptable solution set was calculated a fast messy genetic algorithm (FMGA). After it, the appropriate alternative design was achieved by using Nash's and Young's bargaining models. It's concluded that the obtained alternative for both water distribution networks showed that for constant decision making authorities, use of either Young's or Nash's bargaining models yield the same results. It's also concluded that investors and consumers approximately achieve 86% of their utilities using the same decision-making authority.

Maskit and Ostfeld [8] proposed a method for calibrating the leakage parameters α, β of equation: $q_{k-leak} = \beta_k l_k P_k^{\alpha_k}$, where P is the pressure in pipe k, l is the length of pipe k and q_{k-leak} is the water losses in pipe k. The pipes in the hydraulic network were partitioned according to their properties and for every resulted group of pipes, the α, β values were computed using a genetic algorithm (GA) linked with EPANET, which changed the α, β values to calibrate the hydraulic network. Results were compared with experimental data from the hydraulic network and showed reliable matching for the α, β values.

Puust and Vassiljev [9] compared the performances of a genetic algorithm and a custom research tool (Levenberg–Marquardt) to calibrate (calibrated pipe roughness values and demand/leakage calibration) and update the Tallinn (Estonia) hydraulic network. Before accomplishing the pipe roughness calibration, it was necessary to reanalyze the demand patterns and accomplish some corrections. It's concluded that both calibration tools performed well and the calibration results are comparable with each other to some extent.

Marchi *et al.* [10] presented a method for the rigorous comparison of various algorithms for the optimum design of water distribution systems. The method includes the following steps: (1) selection of evolutionary algorithms (EA) techniques to be compared; (2) selection of appropriate test problems; (3) calibration of each EA algorithm for each test problem; (4) final runs of each EA method on each test problem; and (5) analysis of the results. The techniques of genetic algorithms (GA), particle swarm optimization (PSO) and differential evolution (DE) were applied to two frequently used water distribution systems (WDS) case studies and to a real-size water distribution system consisting of 476 pipes to demonstrate the method. It's concluded that GA can give good results if sufficient function evaluations are allowed. PSO performances were good at the initial stage of the optimization; however, they do not improve markedly for increasing numbers of evaluations. The DE performed well for all three problems and was clearly the best algorithm overall. However, its parameters can span over a large range of possible values. It's also concluded that the algorithm performances depend on the specific problem and the number of function evaluations allowed, that correct calibration is an essential phase for a fair comparison of evolutionary algorithms, the best parameters are a function of the problem characteristics, of the objective function and of the variants in the algorithm operators. Therefore the adoption of configurations tested on slightly different versions of the algorithms can lead to quite different results.

3 Method

It will be presented a method that uses a hybrid model composed of hydraulic network calculation software developed by the authors coupled with a genetic algorithm adapted by the authors to suit their necessities. As aforementioned, the objective of using the genetic algorithm is to optimize hydraulic networks operations when there are valves installed in a hydraulic network. To reach the objective, the head loss coefficients of valves (kv_s) will be the parameters (unknowns) generated by the genetic algorithm. If there aren't any valves in the hydraulic network, the proposed method won't work. Nevertheless, the authors guess that everybody who works with hydraulic networks will agree that the possibility of a hydraulic network without any valve installed in it is almost equal to 0 (zero).

The authors used the following equations to optimize the hydraulic networks operations:

$$P_{min} = \min \sum_{j=1}^{tp} \sum_{i=1}^{nt} fp\, \rho g Q_{ji} \Delta H_{ji} \tag{1}$$

The objective function of the genetic algorithm is given by eqn. (1), where (P_{min}) is the minimum sum of the dissipated hydraulic power of any given hydraulic network for all calculation time steps of the extended period simulation, (tp) is the number of calculation time steps, (nt) is the number of pipes in the hydraulic network, (fp) is the penalty function, (ρ) is the specific mass of the fluid, (g) is the acceleration of gravity, (Q) is the discharge at time step "j" in pipe "i" and (ΔH) is the head loss at time step "j" in pipe "i" (Diniz *et al.* [1]). It's important to mention that all symbols are in the International System of Units.

The imposed restrictions will be the allowable maximum and minimum pressure heads limits on nodes (Hp_{max} and Hp_{min} respectively) and the maximum and minimum reservoir water levels limits (also Hp_{max} and Hp_{min} respectively). If restrictions are not attended, a penalty to the objective function is applied. Penalties are applied by the penalty functions. In eqns (2), (3) and (4), Hp is the pressure head in any node and also the reservoir water level. Penalties are calculated by the following equations (Diniz *et al.* [1]):

$$\mathrm{fp} = 1 \qquad \text{if} \quad \mathrm{Hp_{min}} \leq \mathrm{Hp} \leq \mathrm{Hp_{max}} \tag{2}$$

$$\mathrm{fp} = -\left(\frac{2\mathrm{Hp} - \mathrm{Hp_{max}} - \mathrm{Hp_{min}}}{\mathrm{Hp_{max}} - \mathrm{Hp_{min}}}\right) \quad \text{if} \quad \mathrm{Hp} < \mathrm{Hp_{min}} \tag{3}$$

$$\mathrm{fp} = \left(\frac{2\mathrm{Hp} - \mathrm{Hp_{max}} - \mathrm{Hp_{min}}}{\mathrm{Hp_{max}} - \mathrm{Hp_{min}}}\right) \quad \text{if} \quad \mathrm{Hp} > \mathrm{Hp_{max}}. \tag{4}$$

The internal input data, for the genetic algorithm operators, is the population size, the substring length, the total string length (substring length X number of unknowns), the number of generations to be calculated, the crossover probability, the mutation probability, if it's going to use elitism or not, the scaling constant and the number of unknowns. The total number of unknowns is equal to the number of valves installed in the hydraulic network multiplied by the number of time steps the valves will work in the extended period simulation. Each time step is equal to 1 (one) hour, so it's simple to conclude that the time steps to calculate the extended period simulation will vary from 1 (one) to 24 (twenty four). It's important to say that the user defines the input data for the genetic algorithm.

The main external input data to be yielded by the user to calculate the steady state is the hydraulic network topology, the pipe absolute roughness, the kinematic viscosity and the specific mass of the fluid, the allowable maximum and minimum pressure heads on nodes, the nodal demands, the node elevations, the reservoir water level and the allowable maximum and minimum reservoir water levels. If the extended period is going to be simulated, the main input data is the number of valves, the valves coefficients when they are closed, the number of boosters, data of the booster curve (shutoff head, head for the best efficiency point etc.), the number of time steps to be calculated (at most 24 (twenty four)) and the nodal demands for each time step.

It's important to notice that the purpose of this paper is to show an application of hydraulic network calculation software coupled with a genetic algorithm to optimize hydraulic networks operations. The purpose isn't to explain how the adapted genetic algorithm or developed hydraulic network calculation software works. So, it won't be emphasized the technical terms referring to the genetic algorithm and the equations used in the hydraulic network calculation model. If the reader wishes to know more about these two tools, it's necessary to look for it in Diniz *et al.* [1].

The process begins with the genetic algorithm generating randomly the initial population, that is, the total number of unknowns (kv_S) for each individual for the first generation. It means that if the population is composed of 20 (twenty) individuals, the genetic algorithm will generate 20 (twenty) sets of kv_S, that is, one set for each individual. After generating the initial population, hydraulic network calculation software is called to calculate the hydraulic variables (pressures on nodes, discharges in pipes, reservoir levels, head losses in pipes caused by discharges and valves and friction factors of pipes) for each individual. After calculating the hydraulic variables for each individual, the objective function is evaluated for each individual and the best one is selected, that is, the individual with the kv_s that yielded the hydraulic network with the minimum dissipated hydraulic power sum for all calculation time steps of the extended period simulation for the first generation. The genetic algorithm keeps the best individual of the first generation and then begins to calculate the second generation by creating a new population. After calculating the hydraulic variables for each individual of the second generation, the objective function is evaluated again for each individual and the best one is selected by the genetic algorithm and compared to the best individual of the first generation. If the best individual of the second generation has a dissipated hydraulic power sum littler than the best individual of the first generation, the genetic algorithm replaces the first individual by the second one, keeps it and begin to calculate the next generation, otherwise the genetic algorithm keeps the first individual and begin to calculate the next generation. The process finishes after the genetic algorithm have calculated all generations. After it, it's printed 3 (three) output files. The first one yields the hydraulic variables for the steady state. The second one yields the hydraulic variables for the extended period simulation. The results of the second output file represent the hydraulic network with the minimum dissipated hydraulic power sum. The third output file yields the values of kv_s and the dissipated hydraulic power sum for each generation.

4 Results

Hydraulic network calculation software and the genetic algorithm were tested for the hydraulic network of the city Campo Bom, RS, Brazil. The authors changed the elevations and demands of a few nodes and the reservoir water level from the original scheme of this hydraulic network to suit their necessities.

First, the steady state was calculated and the results showed that nodes 18 and 22 had under pressure problems (in Brazil, the maximum and minimum allowable pressure in hydraulic networks is $50mH_2O$ and $10mH_2O$ respectively). After it, the extended period was simulated having 2 (two) boosters installed in pipes 18 and 36. The results showed that the under pressure problems of nodes 18 and 22 were solved, but on the other hand, nodes 19, 20, 21 and 23 acquired over pressure problems in 4 (four) time steps along the day. To overcome these problems, it was installed 3 (three) gate valves in pipes 21, 23 and 24 as shown in fig. 1. The absolute roughness of all pipes is 0.1 mm. The yielded results will be shown and discussed ahead.

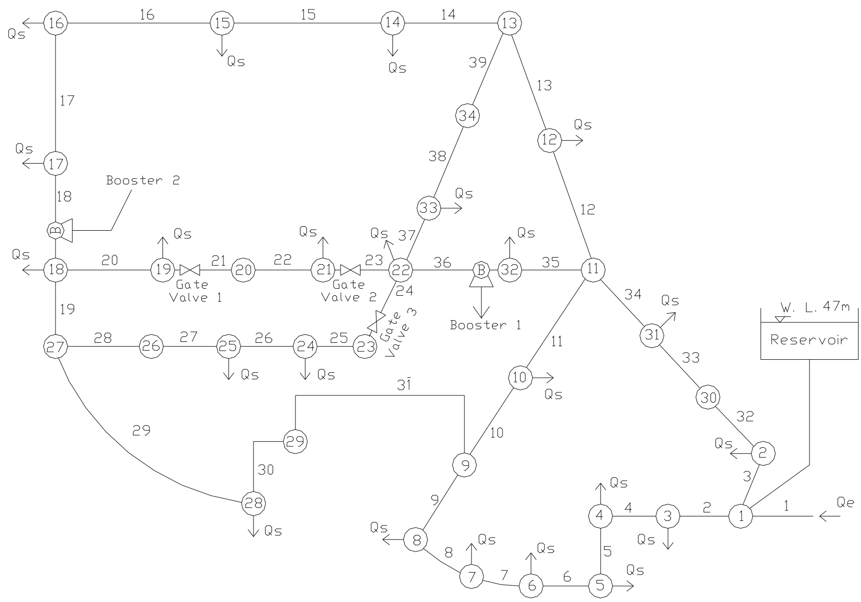

Figure 1: Modified hydraulic network scheme.

As just mentioned, it was necessary to install 3 (three) gate valves in the hydraulic network. When there's at least a valve installed in the hydraulic network, the hybrid model uses the genetic algorithm. The main internal input data for the genetic algorithm was defined as follows: population size: 10 individuals; substring length: 13; number of generations: 1 (one) and 200 (two hundred); crossover probability: 95%; mutation probability: 2%; elitism: applied and scaling constant: 1.5. The number of unknowns (12 for each individual) and the total string length is calculated by the genetic algorithm itself. The values for the input data were chosen because the authors' experience, based on several trials, shows that these values yield the best results, at least for the present problem.

As aforementioned, the user decides how many time steps will be calculated in the extended period simulation. Since there are 4 (four) time steps with over pressure problems, it was decided to calculate the extended period simulation only for the time steps with over pressure problems. It was done because the genetic algorithm takes a long time to yield the results and it would take a very long time if the extended period was simulated for the 24 (twenty four) time steps of the day. This action, of course, brings consequences. One of the consequences is that it was necessary to assume that the reservoir water level changes only in the calculated time steps, that is, between two calculation time steps, the reservoir water level remains steady. To make it clearer, let's imagine that the time steps with over pressure problems occurred at 0:00 am, 6:00 am, 12:00 pm and 18:00 pm. The extended period was simulated only for these time steps and the reservoir level changed only in these time steps. Between 0:00 am and 6:00 am, 6:00 am and

12:00 pm, 12:00 pm and 18:00 pm and 18:00 pm and 0:00 am the reservoir water level was considered steady, since as it was said, the extended period wasn't simulated among these time steps.

It's important to say that besides the hydraulic variables, the second output file also yields the minimum dissipated hydraulic power sum regardless there are or not valves installed in the hydraulic network, the head losses sum caused by discharges, the head losses sum caused by valves and the total head losses sum (discharges plus valves) in the whole hydraulic network for all calculated time steps. It's also important to mention that when the hybrid model yields the results (hydraulic variables) that represent the hydraulic network with the minimum dissipated hydraulic power sum, all nodal demands (input data) are obeyed, all pressure heads on all nodes are between the allowable maximum and minimum pressures and the reservoir water level is also between the allowable maximum and minimum reservoir water levels.

As aforementioned, the number of generations was 1 (one) and 200 (two hundred). The objective of running the genetic algorithm with only 1 (one) generation was to try to simulate a solution without planning the valve openings. This unplanned solution solves the over pressure problems, but it doesn't take into account the consequences this solution cause to the hydraulic network. The other objective was to try to reach the best and worst solution when only 1 (one) generation is calculated and to analyze the consequences to the hydraulic network. When running the genetic algorithm for 200 (two hundred) generations, it yields a solution with optimal valve openings settings.

It was necessary to accomplish several trials because although the genetic algorithm tends to converge to a steady solution, it generally yields a different solution (close to the previous one) each time it's run, especially if the number of generations to be calculated is little.

Observing the values of the head losses sum in table 1, it's noticed that the minimum total head losses sum (374.39mH_2O) is, of course, for the extended period simulation without valves installed in the hydraulic network. Comparing the head losses sum for the best result and for the worst result when 1 (one) generation is calculated to the minimum one, it's observed that the total head loss increased 21.96mH_2O (5.9%) and 51.07mH_2O (13.6%). Comparing the head losses sum when 200 (two hundred) generations are calculated to the minimum one, it's observed that the total head loss increased 10.17mH_2O (2.7%). As aforementioned, the three solutions (valves installed) solve the over pressure problems in the hydraulic network, but when only 1 (one) generation is calculated, the head losses increase too much and it's not good, because ultimately, energy is being wasted, since the head loss unit is, using other words, energy per weight unit. When 200 (two hundred) generations are calculated, the head losses increase as little as possible and ultimately, energy is being saved.

The head loss coefficients (kv_S) values of the valves installed in the hydraulic network which provided the minimum dissipated hydraulic power value obtained for 1 (one) generation (97961.55W) and 200 (two hundred) generations (96252.43W) are shown in tables 2 and 3 respectively.

Table 1: Dissipated hydraulic power sum and head losses sum yielded by the hybrid model.

	dissipated hydraulic power sum (W)	head losses sum (discharges) (m)	head losses sum (valves) (m)	total head losses sum (discharges + valves) (m)
no valves	95135.40	374.39	0.00	374.39
1 generation (best result)	97961.55	382.35	14.00	396.35
1 generation (worst result)	102111.07	391.76	33.70	425.46
200 generations	96252.43	377.16	7.40	384.56

Table 2: Values of kv for the minimum dissipated hydraulic power value – 1 (one) generation (best result).

	Period 1	Period 2	Period 3	Period 4
Gate valve 1	83.21	90.23	31.99	75.23
Gate valve 2	36.45	3.31	27.39	33.26
Gate valve 3	50.34	42.12	94.30	24.14

Table 3: Values of kv for the minimum dissipated hydraulic power value – 200 (two hundred) generations.

	Period 1	Period 2	Period 3	Period 4
Gate valve 1	97.98	96.67	80.36	85.67
Gate valve 2	50.51	0.16	0.34	8.73
Gate valve 3	31.99	21.61	11.65	8.82

Observing the values of table 3, it's noticed that the kv_S values for gate valve 2 are almost 0 (zero) in periods 2 and 3. It means that, in practice, gate valve 2 could be left open in periods 2 and 3. It doesn't happen to the same kv_S values of table 2. This is one of the reasons the head loss increase so much when just 1 (one) generation is calculated. Another reason is because, in a general way, the values in table 3 are much littler than the values in table 2. It's important to notice that the genetic algorithm worked with continuous values instead of working with discrete values. In practice, it would be necessary to adjust the obtained kv_S values for the gate valves, since a gate valve openings are divided in 8 (eight) parts.

5 Conclusions

This paper presented a method to minimize the head losses increase in a hydraulic network by using a genetic algorithm to minimize the dissipated hydraulic power sum in the whole hydraulic network for all calculation time steps of the extended period simulation through optimal valve openings settings. It was concluded that when the valve openings are planned, the head losses increase only the amount necessary to solve the over pressure problems and it prevents energy waste. On the other hand, when the valve openings are unplanned, although the over pressure problems are also solved, the head losses increase beyond the necessary and it wastes energy. It was also concluded that the method worked satisfactorily for the studied hydraulic network. Another conclusion is that this method brings a different approach regarding energy saving, which is directly associated to costs savings.

6 Recommendations

The developed method needs to be tested in other hydraulic networks. It would be good to test the method using other optimizations techniques, since the genetic algorithm takes a very long time to yield the results. As aforementioned, the extended period was simulated only for the time steps with over pressure problems. So, it's necessary, no matter how long it will take, to simulate the extended period for the 24 (twenty four) time steps of the day to analyze if the reservoir will be able to supply the hydraulic water network nodal demands along the day, since there are valves and boosters working and the maximum and minimum reservoir water levels limits need to be obeyed. Other recommendation regards the boosters. When the second output file yields the hydraulic variables for the extended period simulation representing the hydraulic network with the minimum dissipated hydraulic power sum, it wasn't analyzed if the boosters are working far from the best efficiency point. It also has to be analyzed. It's also necessary to test different kinds of valves, since only gate valves were tested.

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