Use of Computational Intelligence for Scheduling of Pumps in Water Distribution Systems: a comparison between optimization algorithms

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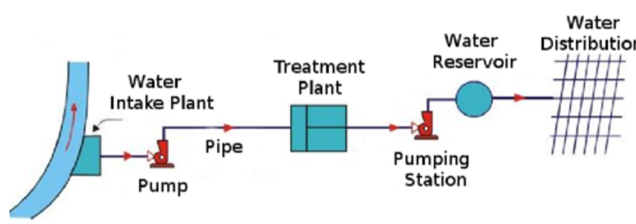
***Abstract*—This work aims to study the operational scheduling of hydraulic pumps in a Treated Water Lift Station (TWLS) using computational intelligence techniques. This scheduling is very important to reduce electricity consumption of TWLS. For the experiments, a typical TWLS composed of two pumps and a reservoir is simulated. The choice of operation periods is obtained to minimize expenses with electrical energy, by means of an optimization task. From the hydraulic power spent, the TWLS electrical consumption is calculated. A factor λ is used to correlate number of pumps starts and corresponding maintenance costs. An electrical consumption function, adjusted with this maintenance factor, is used as the objective function to be optimized. In this context, two meta-heuristics are compared: Simulated Annealing (SA) and a hybrid instance of Genetic Algorithms (HGA). Both meta-heuristic approaches were chosen because the reduction of energy and maintenance expenses can be seen as a nonlinear optimization problem, in addition to both techniques being used successfully to solve several real World problems. A statistical inference based objective comparison is done between results of both algorithms, and SA showed to achieve better results. After optimizing the activities related to this scheduling, it is possible to verify a reduction of up to 28.0% in electrical energy expenses, when compared to actual non-optimized operation.**

***Index Terms*—Metaheuristics; Simulated Annealing; Hybrid Genetic Algorithms; Water Distribution Systems.**

I. Introduction

A Water Distribution System (WDS) is a collective solution to provide water to the community. This system is composed by the set of pipes (main, primary and secondary networks), lift stations, reservoirs, control valves and water meters [5]. It is through a WDS that water is taken from nature, treated and made available to the population. A conventional water supply system is comprised by the collection, adduction, treatment plant, reservation, distribution units and domiciliary networks. Figure 1 shows the main constituent units of a WDS.

Fig. 1: Main subsystems of a WDS.



Source: [5]

Among the subsystems which belong to a WDS, Treated Water Lift Stations (TWLS), or simply pumping stations, play a key role in providing water to the population. Pumping stations correspond to the places where water is pumped up, to be distributed afterwards by gravity to consumers. Figure 2 shows an example of such a lift station. The importance of pumping stations for the supply of water to the community is justified by the fact that the hydrographic basin, in many cases, is on such steep ground that water, in order to reach some points, must be pumped up [20].

According to a survey carried out by the Brazilian National Program for the Conservation of Electrical Energy for Sanitation (PROCEL, in Portuguese), pumping and treatment of water and sewage represents 2.6% of the total consumption of electricity in Brazil. From this total, 90 to 95% is consumed by pumping systems. The remaining percentage is used for lighting and auxiliary systems. Electricity expenditures reach, on average, 12.2% of the total cost of water supply and sewage systems for service providers [17]. The use of optimization techniques in this context can help with a more rational use of energy resources. These techniques can provide an efficient use of electricity and, consequently, the reduction of unnecessary

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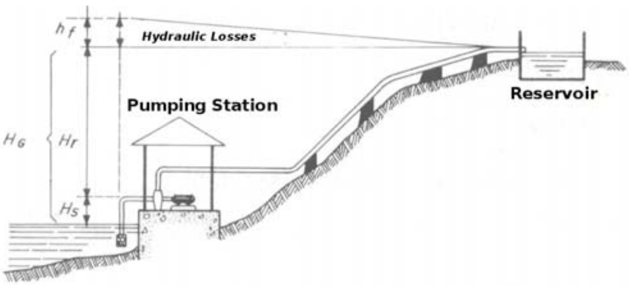
Fig. 2: A Treated Water Lift Station scheme.



Source: [13]

energy costs, ensuring that hydraulic and demand constraints are better met.

The second major expense reported on TWLS is related to pumps maintenance costs [16]. During a scheduled operation, pumps are switched on and off for many times throughout the day. This switching behavior is responsible for electrical energy consumption reduction, but could also increase maintenance costs, provided that it accelerates hydraulic pumps wear and tear [9], [12], [16].

Due to the importance of TWLS for society, a lot of research has been conducted in order to assist in the better use of resources for the distribution of water to the population. [5] uses the multi-objective evolutionary algorithm SPEA to generate operational strategies that reduce the cost of electricity, the quantity of leaks in the water distribution network and maintain the reliability of the water system. [6] also aims to optimize water distribution networks with pumping stations. However, an adaptation of the method proposed by [8] is used to solve this problem. [4] presents a real-time optimization strategy for pumping systems using Genetic Algorithms (GA). GA are also used in the work of [10] to find an optimal points of operation for TWLS. In that work, GA is used to minimize the maintenance costs of pumps, the cost of energy and the level variation of the reservoir. The use of nonlinear programming techniques to optimize pump schedules and minimize energy costs in distribution networks is the focus of the work of [1]. [3] uses PL techniques to solve a mono-objective version of the problem of energy costs in TWLS.

Population algorithms are used in all the stochastic strategies mentioned before. In these approaches, when compared to stochastic algorithms based on local search, they have the disadvantage that, it is often necessary to change optimization variables. In the process of modeling the problem for solution by population algorithms, the understanding of the optimization process becomes, usually, more obscure. Another issue is the slow convergence rate of these algorithms, aside from the computational effort being superior to non-population strategies. Thus, a non-population strategy for the optimization of pumping schedule can be of great value because it is necessary to guarantee the convergence, in real time, of the algorithm, since the service of water supply is primordial for any community. In this work, we will develop an objective comparison between Simulated Annealing (SA) and a hybrid instance of GA to solve the TWLS operation scheduling optimization problem, to verify addressability of both, non-population and population strategies for that specific context. SA [14], [18] and GA [7], [19] were chosen as optimization strategies because both have been used to successfully solve several real world nonlinear and complex problems such as the problem addressed here.

The next sections of this paper are divided into Context Description, Problem Formulation, Methodology, Evaluation Function, Results and Discussion, and Final Considerations. In the Context Description section, the scenario where the optimization problem was used is presented. In the Problem Formulation section, the objective function and the constraints of the proposed optimization problem are addressed. In the Methodology, the parameters used by the optimization algorithms are discussed. The Evaluation Function section describes how the evaluation function employed in this work was proposed. In the Results and Discussion, achieved results are presented, aside from an statistical analysis of the results obtained. In the last section, Final Considerations, a conclusion about the work done is presented, as well as some suggestions for future work.

II. Context Description

This work proposes a solution for a mono objective problem of construction of the operational scheduling of pumps in TWLS. The initial stage for the understanding of the context corresponds to knowing the infrastructure and equipments, and collecting the relevant operational data. These issues in this study come from two important references: the article written by [3] and the work done by [15]. These reports describe very well the infrastructure, equipments and operational procedures of actual small scale WDS and corresponding TWLS. From there, data representing an operational application of TWLS were extracted. Figure 3 represents a sample of data used as hourly demand in the experiments reported below. An illustration of that TWLS, used to the construction of the optimization model, is shown by Figure 4. In this figure, there are two pumps tagged as B1 and B2, and one reservoir. This reservoir has a maximum capacity of water storage $V_{max} = 400.0\ m^3$.

Fig. 3: Sample of weekly consumption demand per hour.

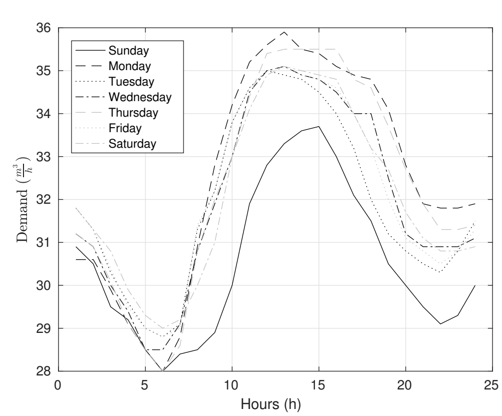
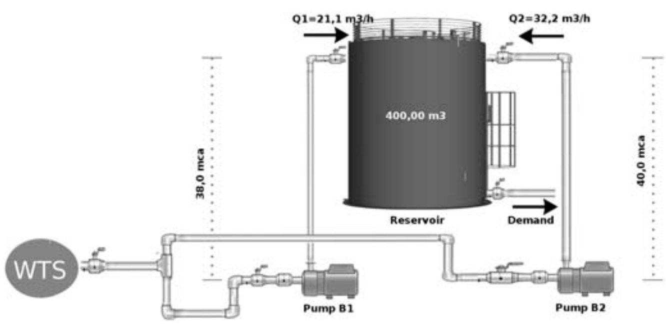


Fig. 4: An actual small scale TWLS plant with two pumps.



In the WDS, water is sent to the reservoir through two hydraulic pumps. Pump B1 has a hydraulic power of $5.516\ kW$, operating at a nominal flow rate of $21.10\ m^3/h$ and a head height of $38.00\ mca$. At the pump head height, the height between the reservoir base (where the pump input is connected) and the pressure losses in the piping line are already computed. Pump B2 has a hydraulic power of $7.354\ kW$ and is located at the same height as pump B1. However, due to the difference in pipe diameters, it has a head height of $40.00\ mca$. The nominal flow rate of pump B2 is of $32.20\ m^3/h$.

From this reservoir, by the difference of quota, the demand of the population is supplied. Both pumps operate at constant power during the day and can be switched on or off. The efficiency considered for each of the pumps is of $\eta = 75\%$. In order to carry out the calculations, it is considered that the input conduit for each of the reservoirs is located at the top, above the maximum level. Thus, the water in the reservoirs does not influence the holding pressure of the pumps. In addition, the pressure relative to the level of the reservoir in the pumps suction is disregarded.

The initial level (V_0) of the reservoir, as well as the minimum ($\frac{1}{3}V_{max}$) and maximum ($\frac{7}{10}V_{max}$), are presented in Table I. For the calculation of electrical energy consumption, the Brazilian seasonal green price was adopted. There are two different rates, depending on the hours of operation of the pumps. Table II presents the correspondent rates to off-peak and peak periods, already discounted the 15.0%, guaranteed by law, received by water and sewage service companies.

TABLE I: Actual TWLS Reservoir Levels.

Maximum Volume (m^3)	400.000
Minimum Volume (m^3)	133.332
Initial Volume (m^3)	280.000

Nowadays, in Brazil, the most used WDS reservoir level control scheme is the classical on-off (or bang-bang) control.

TABLE II: Adopted Energy Prices.

Time	**Rate** ($\frac{R\$}{kWh}$)
Peak time (18:00 to 20:59) - T_2	0.7491
Off-peak times (otherwise) - T_1	0.1409

This scheme uses only two binary level sensors, located at minimum and maximum level positions. When minimum level is detected, both pumps are switched on, and when the maximum level is reached, both pumps are switched off. With this simplified control scheme, neither hour-specific water demands nor different energy rates are observed, and the level control is not able to guarantee that daily demand will be available. It would be desirable to use a more adequate control system, which could take into account lo and medium-term water demands and use of energy constraints, as it will be proposed later in this work.

III. Problem Formulation

As mentioned in Section I, this work aims to find the operating points that minimize the electricity costs of the two hydraulic pumps in the lift station showed in Figure 2. The cost of electrical energy, adopting the green seasonal rates, can be expressed by Equation (1). In this equation, the portions referring to energy expenditures of pumps B1 and B2 are shown in each of both peak and off-peak periods.

$$\begin{aligned} C_{EE} = {} & \sum_{i=1}^{18}\left(\sum_{b=1}^{nb}\frac{\gamma Q_b H_b}{\eta_b}t_{bi}T_1\right) + \\ & + \sum_{i=19}^{21}\left(\sum_{b=1}^{nb}\frac{\gamma Q_b H_b}{\eta_b}t_{bi}T_2\right) + \\ & + \sum_{i=22}^{24}\left(\sum_{b=1}^{nb}\frac{\gamma Q_b H_b}{\eta_b}t_{bi}T_1\right), \end{aligned} \quad (1)$$

where:

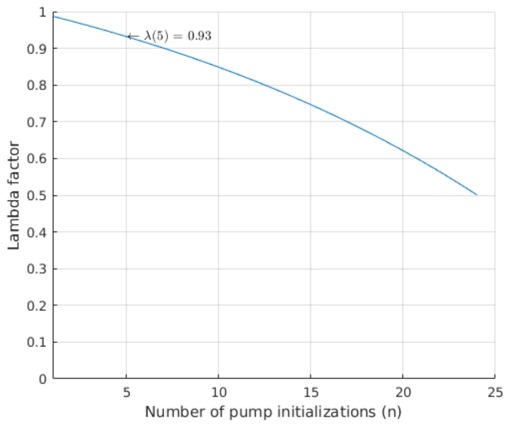
- Q_b: water flow rate (m^3/h) of pump $b \in \{B1, B2\}$;
- H_b: head height (mca);
- γ: water specific weight;
- η_b: efficiency of pump b;
- nb: number of pumps;
- t_{bi}: pump working state (on/off - 1/0);
- T_1: off-peak rate for consumption of a unit of energy;
- T_2: peak rate for consumption of a unit of energy.

Equation (1) is used to minimize the cost of energy in each of the 24 hours of a day. To be able to estimate maintenance costs, a factor λ is used to take into account the number of pump switchings (off/on and on/off) during the period of a day. As the number of switchings increase, maintenance costs also increase. Also, as off-on switchings increase, energy consumption as well increases, see a relationship chart at Figure 5. The resulting decay function of λ is adjustable, as it performs a penalization action to the increase in the number of pump switchings. That one illustrated in the figure was used for the experiments described in Section VI. Then, the former Equation (1), after the correction performed by λ, takes the final form represented by Equation (2):

$$C_{total} = \left(\frac{C_{EE}}{\lambda_{Factor}}\right). \quad (2)$$

In order to ensure that the population's demand is met during the day, volume constraints are included, to better formulate the problem. Inequality constraints aim to maintain the water actual level in the tank in-between the minimum and the maximum desired levels. Those are represented by:

Fig. 5: Lambda factor (λ_{Factor}) - relationship between number of switches and increase of maintenance costs.



1) Maximum reservoir volume:

$$\left(280.0 + Q_1 \sum_{i=1}^{24} t_{1i} + Q_2 \sum_{i=1}^{24} t_{2i} - \sum_{i=1}^{24} d_n\right) \leq 400.0 \quad (3)$$

2) Minimum reservoir volume:

$$\left(280.0 + Q_1 \sum_{i=1}^{24} t_{1i} + Q_2 \sum_{i=1}^{24} t_{2i} - \sum_{i=1}^{24} d_n\right) \geq 133.3 \quad (4)$$

where d_n is the hourly demand.

As the day has been divided into 24 one-hour intervals, each pump operation is limited by one hour. This explains the formulation of the optimization problem presented in the Equation (1). That equation, along with inequality constraints, thoroughly represent the problem to be solved.

IV. Methodology

A. Simulated Annealing

1) Solution Representation: A solution to the problem formulated in Section III is represented by a binary vector V, with 48 positions. Among these positions, the first 24 represent the on/off state of the pump B1 during each of the 24 hours of the day, and the other 24 positions correspond to the on/off state of the pump B2 for the same period. Each of these positions represents one hour of the day. Table III provides an example solution to the problem, using the representation just described.

The solution presented by Table III informs that pump B1 must remain switched on from 17:00 to 17:59 and off during the interval from 18:00 to 18:59. For pump B2, it is indicated that it must remain on in the period from 02:00 to 03:59 and off in the interval from 10:00 to 10:59. Thus, the initial 24 positions represent the 24 hour working time of pump B1, and the other 24 positions of the vector V correspond to 24 hour working time of pump B2.

TABLE III: Typical solution to the formulated problem.

01:00	**02:00**	**03:00**	**...**	**10:00**	**11:00**	**...**	**23:59**
0	0	0	...	1	1		1
01:00	**02:00**	**03:00**	**...**	**10:00**	**11:00**	**...**	**23:59**
0	1	1	...	0	1	...	0

2) Algorithm Details: For the solution of the minimization problem, the Simulated Annealing (SA) algorithm is used. In SA algorithm, the metal annealing process is simulated. The cooling of metals must occur slowly, so it is possible to generate more stable and structurally stronger elements. At each iteration of the algorithm, a new state is randomly generated from the current state. If the generated state has lower energy than the current state, it becomes the current state of the system. However, if the new state has higher energy than the current state, it still has a probability of being chosen as the current state. At high temperatures, each state has approximately the same probability of being chosen as the current state. As the iterations pass, the temperature is reduced and the states with lower energy become more likely to become the current state. The method ends when the temperature approaches zero.

At the beginning of the cooling process, the temperature is high to increase the probability of accepting worsening solutions and thus prevent the method from getting stuck at unattractive local optima. As the temperature decreases, the probability of accepting solutions that generate worsening values is reduced. At the end of this process, the probability of acceptance worsening solutions becomes close to zero, which evidences the finding of an optimal solution, possibly global one. In order to ensure that the final response of the method corresponds to an optimal solution in relation to the given neighborhood, the descent method with the best improvement strategy is applied.

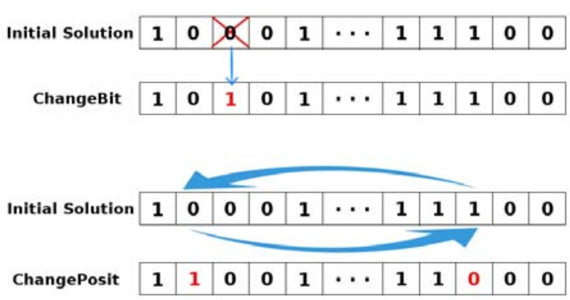
For the use of the SA algorithm, it is necessary to define the input parameters ($f(.), N(.), \alpha, SA_{\max}, T_0, s$), as well as which method is used in the neighborhood calculation. The parameter α is well studied in the literature. Some authors indicate that the cooling rate should be small enough, so $\alpha = 0.998$ was used. The cooling used corresponds to the geometric prescription. The maximum number of iterations allowed for each iteration, $SA_{\max}$, was chosen experimentally. The value found was $SA_{max} = 150$. The initial solution and the initial temperature (T_0) were generated according to Subsections IV-A3 and IV-A4, respectively.

3) Determination of Initial Solution: The initial solution is generated here at random. This solution is used to calculate the initial temperature in the iterative algorithm proposed by [2] and also to initialize the SA algorithm. The initial solution represents a random binary vector of 48 positions.

4) Determination of Initial Temperature T_0: The initial temperature is determined through an iterative algorithm proposed by [2]. The parameters used by this algorithm are: minimum acceptance rate of neighbor solutions $\gamma = 0.95$, rate of increase of temperature $\beta = 3$, random initial solution and initial temperature $T_0 = 1$. In addition, the movement used to generate a neighbor consists of exchanging one bit of the initial vector.

5) Neighborhood: For the exploration of the search space, two different types of moves were used separately. The first move consists in performing the exchange of the value of the bit (0 or 1), of only one position of the vector. The second move consists of changing the value of the bit of a position by the value of the bit in another position. These moves define, respectively, the Bit-Exchange and Position-Exchange neighborhoods. Figure 6 illustrates the moves used. These moves are used in order to generate new solutions for the SA and therefore explore the search space. In order to indicate which move will be used in SA, 30 experiments are performed for each move. The result achieved by the SA with the use of each movement is statistically compared. These experiments are aimed at finding out what type of movement generates solutions with lower energy consumption and, therefore, the winning move will be used in SA.

Fig. 6: Moves in an example solution.



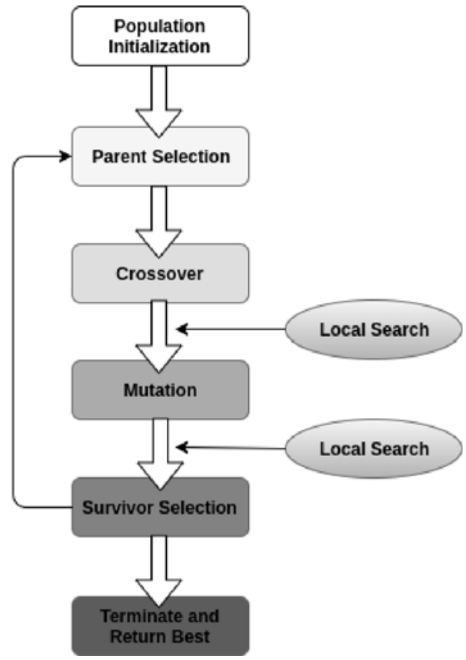
B. Hybrid Genetic Algorithm (HGA)

Genetic Algorithm (GA) is a search-based optimization technique based on the principles of evolution and natural selection. This approach is frequently used to find optimal or near-optimal solutions. Unlike SA, GA is based on population dynamics. Both techniques (SA and GA) are used to solve the pump scheduling problem and the results obtained are compared. Figure 7 shows how an hybrid version of GA, here referred to as HGA, was implemented. HGA combines a classical GA algorithm with two local search procedures executed after crossover and mutation, for each individual at each generation of population evolution. Its clear computational overhead is expected to achieve better results than the classical algorithm, by means of local searches. An example of hybrid algorithm approach, which aims to solve a real problem, is presented by [11].

1) Population Initialization: HGA uses the same binary representation used by SA. The first population is chosen in two steps. In a first step, 100 solutions are randomly chosen. After that, in step two, in 30% of these random solutions, a local search with the best improvement strategy is applied. The purpose of these two steps is to generate a diversified initial population that contains individuals of good quality.

2) Parent Selection: Parent selection is a process of selecting parents which combine and recombine to create new solutions for the next generation. This work uses a process called Roulette Wheel Selection (RWS). In RWS, parents are

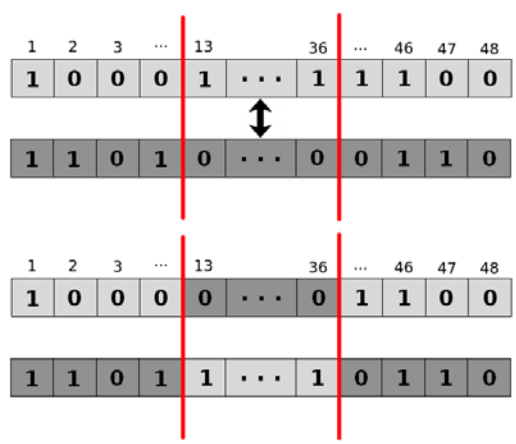
Fig. 7: Steps used to implement HGA.



divided into n pies, where n is the number of individuals in the population. The length of each piece of these pies is proportional an individual fitness value. So, parents with large pieces of pie represent better solutions, and then have greater probability to be chosen as a parent.

3) Crossover and Mutation: After choosing two parents, we must decide if they will generate two new individuals or not. The crossover probability is chosen to be 85%. This operator is performed with two points-crossover, as presented by Figure 8.

Fig. 8: Two points crossover.



Mutation occurs at a rate of 5%. When this happens, one position of the solution is, randomly, chosen and your bit value is changed.

4) Survivor Selection and Termination Condition: Survivor selection determines which individuals are to be kicked out and which are to be kept in the next generation. Therefore, the Fitness Based Selection (FBS) is used, where children replace the worst fit individuals in the population. FBS works as follows: first, 5 individuals are randomly selected. After that, a tournament is performed with these 5 individuals, and the 2 worst fit are kicked out. Then two children, obtained by crossover, replace the individuals that were removed.

The stopping condition occurs when the generation number is greater than 1000 or when the difference between best solutions fit, obtained after two consecutive generations, is less than 0.01.

V. Evaluation Function

Since the formulated problem presents inequality constraints, a penalization technique is used. Thus, in the objective function, expressed by Equation (1), the minimum and maximum volume restrictions for the tank are added. Equation 5 presents the evaluation function used by SA algorithm.

$$f_a = C_{total} + \rho_1 \times Eq_{vmax} + \rho_2 \times Eq_{vmin}, \quad (5)$$

where:

- C: total cost, in Brazilian Reais, for system operation [Eq. (1)];
- Eq_{vmax}: represents the quantity exceeding the capacity of the reservoir [see Eq. (3)];
- Eq_{vmin}: represents the volume of water that is missing to reach the minimum volume of the reservoir [see Eq. (4)];
- $\rho_1(R\$/m^3)$: penalization, in Brazilian Reais, for each m^3 of water above the maximum limit;
- $\rho_2(R\$/m^3)$: penalization, in Brazilian Reais, for each m^3 of water below the minimum limit.

As the penalization technique is used, the values to be applied for ρ_1 and ρ_2 must be chosen. The choice of these values was performed experimentally, because if high values are chosen, for the evaluation function, it can cause the reduction of the search space. On the other hand, if the values are small, it is possible that infeasible solutions to the problem are generated. Thus, it is necessary to find a trade-off for choosing the values of ρ_1 and ρ_2.

VI. Results and Discussion

For all the experiments following, the hypothesis of normality of the data was verified by means of the Kolmogorov–Smirnov test. Firstly, Equation (5) was tested with two different types of weights. In this test, 30 results obtained with $\rho_1 = 20$ and $\rho_2 = 10$ were compared with other 30 tests performed with $\rho_1 = 2$ and $\rho_2 = 1$. As it can be seen at Table IV, the choice of these weights can directly influence the performance of SA and HGA algorithms.

Table IV displays an Analysis of Variance (ANOVA) for SA test. As it can be seen, the performance of the algorithm is influenced by different values of weights. A Tukey test (not shown here) demonstrated that, with smaller values for weights, SA and HGA present better performance for pump operational scheduling problem solution.

The performances of SA and HGA are compared using the configuration of smaller weights. Both algorithms are executed

TABLE IV: ANOVA test for different ρ in SA and HGA.

	SA	HGA
F_{test}	15.41	6.29
P_{value}	0.0002	0.0152

30 times and the results are presented in Table V, showing that there is statistical evidence to reject the hypothesis of equality of performances for the two algorithms. Then, a Tukey Test result (see Figure 10) demonstrates that SA is a better option to find the optimized pump scheduling, for the TWLS in question. Despite the longer runtime, the algorithm chosen as the best to solve the pump operational scheduling was SA, because its best result reduces in 16% the pumping costs. Table VI summarizes the performance obtained by both approaches (SA and HGA). As can be seen, for all chosen metrics, SA algorithm presents better results than HGA.

Another important feature of using SA to find a pumping schedule is the lowest variance obtained. This feature, shown by Figure 9, is essential for real applications, because it is necessary that the algorithm always generate results, as close as possible to an average value. The best value found with HGA is only 2% higher than the best result obtained with SA, but this value is 16% lower than the average result found by HGA. Therefore, using SA increases the chances that, at each execution, the final pumping costs are lower.

Fig. 9: Boxplot for performance comparison between SA and HGA.

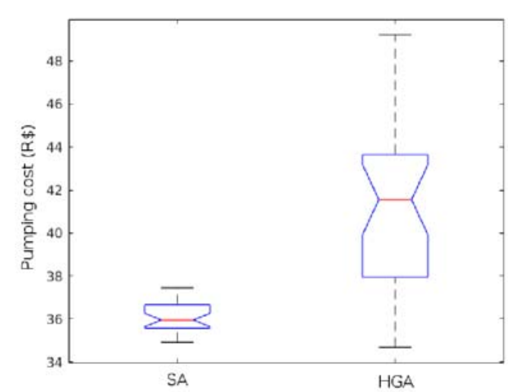


TABLE V: ANOVA test for performance comparison between SA and HGA.

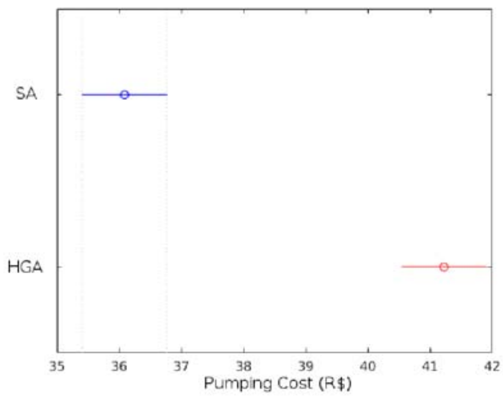
	Value
F_{test}	56.16
P_{value}	4.326^{-10}

Figure 11 presents a pump operational scheduling for one day, obtained by SA. In the interval between 19:00 and 21:00,

TABLE VI: Performance comparison between SA and HGA.

	SA	HGA
Lowest Pumping Cost Found	R$ 34.89	R$ 35.40
Pump Switches	7	10
λ_{Factor}	0.900	0.849

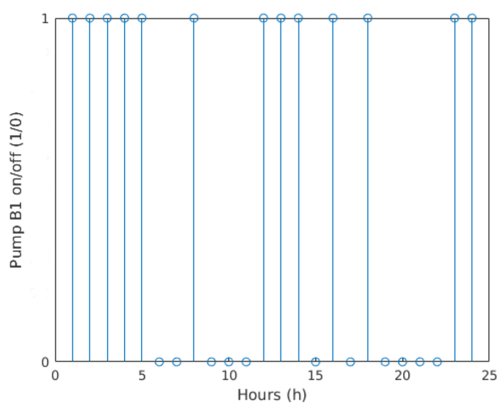
Fig. 10: Tukey test for performance comparison between SA and HGA.



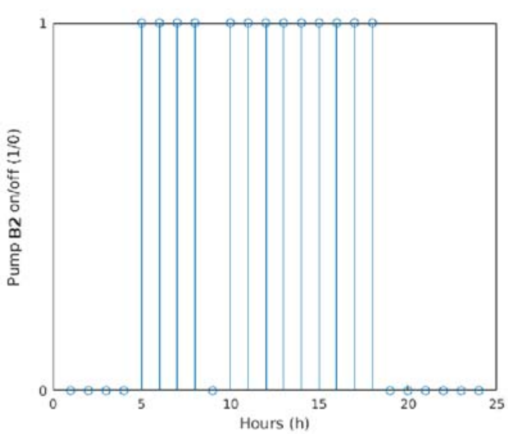
both pumps are kept off. This happens because this interval represents the most expensive energy rates.

Fig. 11: Result of pump operational scheduling applying SA.

(a) Pump B1 scheduling.



(b) Pump B2 scheduling.



To better understand the scenario, the daily total pumping cost, using the schedule presented by Figure 11 and the Brazilian seasonal green price of electric power, reaches R$34.89. When using a bang-bang control scheme with a simple logic that reduces the expenses with electricity, for the same system, without any optimization algorithm, a value of R$48.70 is found. Thus, with the use of SA, it is possible to reduce consumption by up to 28%. It is important to note that the TWLS used in the experiments is considered to be of very small factor, so this consumption economy can become very expressive in the case of big city stations.

VII. Final Discussion

The operational scheduling of hydraulic pumps in a TWLS was studied in this work. Through the use of two different metaheuristics, it was possible to reduce the costs of electric energy spent in such pumping systems and to achieve, for the described scenario, a saving of up to 28% of energy. In large urban centers such as capitals and metropolitan areas, there are a large number of TWLS. As energy costs account for a relevant part of all water and sewage service providers' expenditures, this reduction can generate significant savings for these companies. Therefore, with the adoption of the strategy described in this paper, it is possible to reduce energy expenditures and, nonetheless, to guarantee an efficient and cheaper water supply for the population. The main contribution of this approach is to provide a complete solution for a relevant problem in the area of water distribution, a more comprehensive and efficient approach than similar ones published before, reducing expenditures on energy and maintenance through the adoption of metaheuristic techniques.

As can be seen, some simplifications in the construction of the model, present in section II, were adopted. Constant pumping rates throughout the operating period, no change in load losses during pumping and preventive maintenance schedule are not considered in the model. The introduction of these variables can be explored in future approaches in order to make the problem closer to a real scenario.

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