1. **INTRODUCTION**

There is an effort in investigating new technological innovations aiming at improving the energy efficiency of the several production sectors, which also applies to water supply companies (BRAGHIROLI, 2011; COSTA and RAMOS, 2010). Energy consumption due to the pumping systems represents the biggest parcel of the energy expenses in the water sector - sometimes up to 90%, according to GRUNDFOS (2004) - and there are several practical solutions which can enable a reduction in these costs. Pump and motor upgrades to more efficient solutions, either being technologically more advanced or because they are more properly adjusted to the system, oftenly allow significant energetic savings (TSUTIYA, 2001). Also, changing the pumping operational procedures is very effective since it does not need any additional investment and because the economy with the reduction of the energy cost occurs immediately. According to TSUTIYA (2004), the consumption of energy in most of the water systems all over the world could be reduced by at least 25%, only by improving the performance in terms of energy efficiency.

Operators of the water supply networks have a complex task in taking into account the distinct goals involved in this process. Determining operational rules that watch out for the quality of the service and that are also energetically economical, among an extensive set of possibilities, requires the utilization of models which take into consideration these elements (FILHO, 2006).

Technological advances in the computational area enabled an increase in the quality of the scientific works related to model optimization, as well as reducing the energy cost of operation. Initially, investigations related to cost optimization of pumping costs relied on operational research techniques as, for instance, linear programming (JOWITT; GERMANOPOULOS, 1992; BURNELL et al, 1993), integral linear programming (LITTLE; MCCRODDEN, 1989), non-linear programming (CHASE; ORMSBEE, 1993; YU et al, 1994) and dynamic programming (STERLING; COULBECK, 1975; LANSEY; AWUMAH, 1994). Wood and Reddy (1994) were the first to utilize genetic algorithms (GA) to reduce the energetic cost of pumping systems. These algorithms can be used as heuristic optimization models for achieving the best energy policy to be applied in a water supply system (WSS), enabling the determination of the optimal scheduling of control settings of pumps throughout each day.

The goal of this investigation was to analyze a WSS, model it accordingly and simulate several scheduling scenarios with optimized pumps in order to minimize the expenditure related to energy consumption, based on the demand patterns and associated energy tariffs.

2. **GENETIC ALGORITHMS**

2.1. **Nature and applications**

Genetic algorithms are stochastic methods of search that begin with a population of random chromosomes, which represent different solutions. The basic principles of the GA, widespread by GOLDBERG (1989), are inspired in Darwin’s evolutionary concept of survival of the fittest, evaluating each generation of individuals and allocating reproductive opportunities in such a way that those which represent a better solution to the target problem are given more chances to reproduce than those which are poorer solutions, numerically quantified as their fitness (WHITLEY, 1993). Convergence occurs as the chromosomes evolve to best fit the constrains of their environment.

These algorithms are commonly used to find optimal solutions in complex systems such as the scheduling of supply systems, where the amount of variables leads to vast possible solutions. There are a certain number of initial parameters that can be tuned, prior to the simulation, that affect the quality of the convergence.

2.2. **Initial parameters**

Variations in the parameters that allow the GA to be tuned prior to the simulations influence the conver-
gence process. In the current study, the main parameters considered were the population size of each generation, the elite population size in each one of them and the stopping criteria of the algorithm.

**Population size (PS)**
It represents the number of individuals with different chromosomes that are created each generation. Smaller PS increases optimization speed, but reduces reliability as there might not be enough genetic variety and only a less optimal part of the solution space is explored. On the other hand, too many chromosomes slow down the GA convergence, (KOLJONEN and ALANDER, 2006) and research shows that, after some limit, increases in population size do not yield better results.

**Elite population size (EPS)**
It represents the amount of fittest individuals from each generation that will be automatically chosen for the next one without being subject to crossover, whereas the rest of the population is recombined probabilistically according to their fitness. This increases the performance of the GA, as it prevents the best found solutions to be lost if they were to be recombined. Nevertheless, increasing this value too much may lead to premature convergence to local optima, as the probability of reaching potential better solutions that might have resulted from crossovers is reduced.

**Stopping criterion (SC)**
Given the stochastic character of the GA's, there are no mechanisms to determine the achievement of the optimal solution. Therefore, GA optimization requires heuristic stopping criteria. In this study, that is determined after a limit number of generations without fitness improvement. There is no definitive way to determine the limit number of generations, since running one more might yield a better solution than the one previously found.

### 2.3. Best practices

**2.3.1. Minimizing the solution space**

In pump scheduling it is possible to calculate the solution space ($S_s$) given the number of possible decisions ($n_d$) and the number of pump speed settings ($n_s$), where the total solution space can be determined as being $S_s = n_s^{n_d}$. For instance, if the goal was to determine the solution space for two scenarios, one with 1 pump and the other with 2 pumps, with 2 possible drive speed settings each, in a 24 hour period with 1 hour discrete steps, the total would be $2^{1 \times 2^4}$ and $2^{2 \times 2^4}$ possible combinations, respectively.

The previous example points out that it is not immediately obvious that the size of the solution space in optimization problems can quickly grow to overwhelming sizes. The difference of adding one more pump increases the solution space from $16,777,216$ to $281,474,976,710,656$ possible solutions.

It is therefore important to consider the following when setting up a pump scheduling optimization problem (BENTLEY, 2009):

1. Keeping the number of pumps to a minimum
2. Keeping the number of speed choices to a minimum
3. Considering an initially coarse speed setting and follow that up with progressively refined speed settings.
4. Considering optimizing the shortest duration possible, such as a 24 hour period being able to produce a repeatable schedule.

**2.3.2. Minimizing the trial solution time**

Any improvement that can be made towards reducing the duration of each individual simulation directly reduces the GA's overall run time. Methods that should be considered include:

1. Keeping the model size small, since the more hydraulic elements in a model, the larger the solution matrix that needs to be solved.
2. Keeping the model simple, since the more complex it is (e.g., complicated control regimes), the longer a simulation will take to run.

**2.3.3. Planning to do multiple runs**

The nature of GA's implies that it has an inherent randomness associated with it (WHITLEY, 1994).
Therefore, two optimization runs that are otherwise identical except for one minor change (e.g., larger PS) will in all likelihood produce different optimized solutions. This is more likely to be the case the larger the solution space of the problem. It is a good practice to run multiple optimizations changing nothing other than one or more genetic algorithm parameters to ensure that the best optimized solution is really the best that can be achieved.

3. CHARACTERISTIC CURVES

The pump characteristic curve describes graphically the relation between flow rate and total head for a specific pump (Figure 1). Other important information are also included, such as pump curves for different impeller diameters, net positive suction head curve (NPSH) and the efficiency and power curves (QUINTELA, 2002).

In the case of the Grundfos® NB/NK type pumps, their designation determines its specific nominal discharge port diameter, in couple with nominal and actual impeller diameters (for the top curve in Figure 1, 50, 160 and 177 mm, respectively). The pump’s efficiency throughout its characteristic curve varies and should not drift too much from the best efficiency point (BEP). The motors rotating the shaft that moves the impeller, whose pole number is referenced in the pump designation, also have their own efficiencies that must be considered.

The operation point in the pump curve is dependent upon the characteristics of the system in which it is operating. The system head curve is the graphic representation of the energy equation, or the relationship between flow and hydraulic losses in a system. Figure 2 shows that, by plotting both the system head curve and pump curve together, the pump’s operating point \((\dot{Q}, H)\) can be determined.

When two or more pumps are arranged in parallel, their resulting performance curve is obtained by adding their flow rates at the same head as indicated in Figure 2. The operating point at the intersection of
the resulting curve \((Q_2, H_2)\) represents a higher volumetric flow rate than for a single pump and a greater system head loss. In the case of two similar pumps, because of the greater system head, the volumetric flow rate is actually less than twice the flow rate achieved by using a single pump (QUINTELA, 2002).

When using pumps with operation points next to their BEP \((Q_1, H_1)\), it is not recommended to run them in parallel, since they will be operating at less efficient flows \((Q_{2,1}, H_2)\).

The affinity laws expressed in Eq. (1) represent the mathematical relationship between the speed \((n)\), discharge \((Q)\), head \((H)\) and water power \((P)\) of a pump.

\[
\frac{n_1}{n_2} = \frac{Q_1}{Q_2} = \frac{H_1^{\frac{1}{2}}}{H_2^{\frac{1}{2}}} = \frac{P_1^{\frac{1}{2}}}{P_2^{\frac{1}{2}}}
\]

There are different ratios between the pump’s speed and the other variables. A reduction of 10% in pump speed translates into a 27% reduction in power consumption. It must be noted that this also reduces the pump head in 19%.

For variable speed driven (VSD) pumps, small speed variations of the shaft – directly proportional to the flow – translate into significant pump power variations, which can increase the efficiency of the pumping operation when compared to pumps equipped with fixed speed drives (FSD). Nevertheless, this also affects the pump head, rendering it inoperable below the point where it will not cross the system curve.

Below a certain speed the pump curve may intersect the system curve twice. According to QUINTELA (2002), as these two points come closer and the two curves become increasingly tangent to each other, the operation of the pump becomes extremely unstable if transient regimes occur. Besides, the pump curve can have a shut-off head inferior to the system curve, meaning that the pump is not able to start at that particular speed without a bypass.

4. CASE STUDY AND MODELLING

4.1. Water supply system selection

The supply system for this case study was chosen following the investigation of COSTA and RAMOS (2010) serving the demands of the Fátima region, in Portugal. In reality, the pumping station is comprised of two Grundfos NK 65-250 type pumps with an average pumped flow of 42 l/s, with an overall efficiency of 60%. Since the goal was to test a better type of GA, the pump curve utilized had a constant discharge for all heads and the efficiency was invariable. Thus, these simplifications imply that the data obtained in terms of energy cost should be considered less than accurate, but nevertheless relevant, proving that GA scheduling optimization can improve considerably the efficiency of a pumping operation.

Figure 3 represents the WSS modelation. The water is pumped through a 250 mm diameter pipe with a Hazen-Williams roughness coefficient of 145, spanning for 1,607.8 m and connecting the Cascalheira reservoir (elevation: 375.3 m) to the Fazarga tank (405.0 m).

![Figure 3 – Computational model of the pump system](image)

The tank has a volume of 347.0 m³ when full, but it operates only beyond a 45.3 m³ minimum reserved for emergencies, and therefore the effective total is of 301.7 m³. For this study the average daily consumption is of 19 l/s, which represents an average of 4 hours and 24 minutes of available water with a full tank.

Node N-3 was considered the consumption node, simulating the daily water demand variation, based on information from sensors placed downstream the Fazarga tank. There must be also an energy tariff associated with the model, so the simulation can calculate the energy consumption.

According to LANSCY and AWUMAH (1994), increasing the number of actions per operational cycle proportionally increases the wear of the pumps. Therefore, this value was limited to a recommended daily maximum of three cycles per pump.
4.2. Simulation scenarios

Two distinct models were considered to simulate the studied system. These have different model complexities and solution spaces, as well as particular operational modes:

Two pumps with three starts (2 pump/3)

This scenario comprises two pumps, operating independently from each other with a maximum of three start/stop cycles per pump per day. It allows more versatile solutions as the pumps can operate in parallel with independent speeds at the same time, but it is also the option with the biggest solution space and system complexity of all. In addition, when two pumps operate in parallel, the overall operation point changes a potential less efficient one if the pumps are already correctly dimensioned to operate near their BEP.

One pump with 6 starts (1 pump/6)

This scenario comprises one pump which can start up to six times per day, emulating two pumps with three starts each but which can’t operate simultaneously. When the pumps are prevented to operate in parallel, it guarantees that the pumping occurs always at the same operating point. Therefore, the computational model has to balance the equations for only one pump, which reduces the simulation time. Furthermore, the solution space is also considerably reduced, along with versatility loss in the potential operational strategies.

In Table 1 lies a comparison between solution spaces of these scenarios when combined with both FSD and VSD scenarios. These actions vary between a simple On/Off operation to the possibility of intermediate speeds in a pump equipped with a VSD motor. It must be also noted that, in simulations with four intermediate speeds, the 1 pump/6 approach has almost five quintillion times less possible solutions that its 2 pumps/3 counterpart.

<table>
<thead>
<tr>
<th>Scenario</th>
<th>$S_s$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1 pump/6</td>
<td>Off/On</td>
</tr>
<tr>
<td>2 pump/3</td>
<td>Off/I</td>
</tr>
</tbody>
</table>

Table 1 - Solution spaces for each simulation approach for 1 h time steps in a 24 h period

4.3. Selection of the pump and motor

The total supply needs of the population must be met by the operation of only one pump, whereby the discharge flow must be superior to the average daily demand (20 l/s < $Q$ < 40 l/s), having been also considered pumps with a flow up to double that value. In relation to the total head, the pumps should comprise a range which take into account the increase in roughness of the pipes over time (32 m < $H$ < 38 m).

Based on the NB/NK pump curve catalog from the Grundfos, Figure 4 highlights the fact that the pumps used by Veolia do not seem appropriate for this WSS and are probably operating with reduced efficiency. With a pump efficiency at BEP of 72.5% and considering a motor with 92% efficiency, the total efficiency at that point is of 66.7%. Since the operating point is far from the BEP, a total efficiency of 60% was determined as reasonable. The operational cost resulting from energy consumption was of 22.2 €/day (12/07/2007).

Three pumps which fitted the considered flow and head ranges were selected for testing (Figure 5).
• Pump 50-160/177 does not seem appropriate, since the pump curve extracted from the catalog does not intersect the system curve, meaning that it would operate with flows which are not recommended by the manufacturer;

• Pump 50-160/167 has a discharge flow near to the average daily demand, increasing its probability of becoming obsolete if the demand is intensified or if the flow is reduced due to a pipe roughness increase over time. The maximum efficiency is also inferior to the 65-160/177 and, if equipped with a VSD, the possible speed range is minor given its inferior total heads.

The selected pump for comparison with the current one was, therefore, the 65-160/177 equipped with a 2 pole motor (X1).

It is relevant to determine the speed range in which this pump can operate, so the solution space does not include unnecessarily unfeasible solutions, which is determined by comparison to the system curve. Attending to the affinity laws, Figure 6 shows that in order to avoid system instability, the minimum motor speed should be of 87%.

The commercial software used for these simulations was Bentley’s WaterGEMS, which has embedded in it a genetic algorithm simulation module (Darwin Scheduler).

5. RESULTS

5.1. General considerations

It is always preferable to operate the pumps at off peak hours, as the pumping costs due to electricity consumption for the same volume are inferior. A sufficiently large tank would have enough storage capacity to be filled during those periods, avoiding pumping during peak hours. Two different approaches were studied in order to cope with the fact that the volume of the tank is limited. The demand curve and energy tariff have a repetitive 24 h pattern, thus a daily cycle was considered in the simulations. Thus, the tank must finish the cycle with the same water level as it began, in order to prevent volume variations throughout the days.

The commercial software used for these simulations was Bentley’s WaterGEMS, which has embedded in it a genetic algorithm simulation module (Darwin Scheduler).

5.2. Manual override approach

In order to be properly compared with the existing scenario, the model was tested with a simulation us-
ing the original operational scheduling using the original pump ($X_0$) and the 65-160/177 pump ($X_1$). Subsequently, a manual optimization approach was carried out with the goal of determining an operational strategy which sought to restrict operations during peak and semi-peak hours, while guaranteeing a stable supply. The next step was to broaden those intervals during which the pumps were not operating.

The energy cost of operation obtained from the calibration (22.1 €/day) was similar to the real data provided by Veolia (22.2 €/day), corroborating the reliability of the hydraulic simulation model. This operational regime imposes five pump starts, which probably means that the two pumps took turns so that the daily three starts limit is not exceeded.

In Figure 7, the utilization of pumps in peak hours (from 12:00 h until 13:00 h and from 21:00 h until 22:00 h) can be verified. Pump $X_1$ operates with a total efficiency of 78.9%, a 13.9% difference comparing to pump $X_0$. Pumps $X_0$ and $X_1$ operated with discharge flows of 41.8 l/s and 38.7 l/s, respectively.

Pump $X_1$ managed to complete the daily cycle within the maximum and minimum limits of the tank, operating with a discharge flow similar to the $X_0$ and finishing without tank volume variation (Figure 8). The operational cost of the pump (15.1 €/day) was 32.0% less than the one practiced by Veolia even without an optimized scheduling pattern, which is probably related to an increase in pump efficiency.

After the verification of these results, the heuristic manual optimization was performed operating only one pump at each time and with FSD motors. This strategy can be inferred from Figure 9 for each pump. From Figure 10 it is possible to conclude that both pumps operated within the tank limits, completing the daily cycle without volume variation.
The operational costs of pumps X0 and X1 are of 17.5 €/day and 13.1 €/day, less 21.1% and 41.0% than the initial scheduling strategy respectively.

5.3. Genetic algorithm approach

This approach tests thousands of simulations in order to select the fittest of all given the system in which they are. Harnessing the applicability of these algorithms in complex scenarios, in these simulations two parallel pumps were allowed to operate, which represents an increase in versatility when compared to the manual override approach. Since the software could not simulate the original pump curve due to its mal-adjustment to the system at issue, no GA simulations were performed for this pump.

With VSD pumps it was allowed a total of six possible actions: pump turned off, minimum speed, three intermediate speeds and maximum speed. The tradeoff was to allow some continuity in the speed steps while minimizing the solution space. The model was restricted by the number of pump starts and the tank minimum and maximum water levels, and the heuristic stopping criterion was a maximum of 200 generations without solution fitness improvement.

In the original COSTA and RAMOS (2010) investigation, all the daily cycles started at 0:00 h for an initial tank water level of 2.00 m. This fact implied that the algorithm should guarantee that level at that specific hour, even if it would mean to pump at least advantageous periods. Thus, four different initial water levels were tested for each pump and motor - 0%, 25%, 50% e 75% of the effective volume, that is, 0.30 m, 0.80 m, 1.30 m e 1.80 m, respectively.

In order to overcome the inherent randomness of the convergence of the GA, four different simulations were performed for each water level and pump/motor type, varying the initial GA parameters with a PS of 100 and 200 individuals and EPS of 10 and 20 individuals. The total number of performed GA simulations resulting from these combinations was of 96.

Figure 11 and Figure 12 show the daily cost results for each scenario and water level considered. It is immediately visible the influence of both initial tank water level and initial GA parameters from the scattered results. This is more pronounced in the FSD results (Figure 11), where the minimum result achieved was of 13.3 €/day by comparison to a maximum of 16.5 €/day.

Figure 13 and Figure 14 present the results for the best solutions achieved. The daily operational cost was of 13.1 €/day and 12.6 €/day for the X1 pump with both FSD and VSD motors, respectively. When analyzing the VSD motor results, it can be concluded that the increase in versatility of solutions allowed by this
motor compensates its inferior efficiencies. The fact that the pump operates at lower speeds – it never reaches maximum speed - and only has need for 3 daily starts becomes an advantage in terms of pump life expectancy and maintenance when compared to the FSD, which operates at maximum speed and has 4 daily starts.

It is possible that the worst results obtained for the FSD are justified by the difficulty in matching a daily cycle without volume variation for 1 h control intervals. Also, the VSD can better adapt the supply to the demand by varying flow, reducing power as necessary.

![Figure 13 – Energy tariff and pump power consumption for the best AG solution](image)

![Figure 14 – Flow and tank water level for the best AG solution](image)

6. CONCLUSIONS

The solutions obtained from the various optimization processes produced considerable superior results when compared to the original strategy (Figure 15), with the best solution allowing savings of 43.7%. It would be relevant in future investigations to make a cash-flow analysis of the option of installing new pumps, as well as to introduce integrated dynamic monitoring systems which would allow a real time optimization of the scheduling of the pumps, both in new projects and in existing WSS.

![Figure 15 – Final results for the daily energy cost of operation](image)

The correct utilization of a GA simulator in an optimization process requires running several scenarios, in which the individual duration of each evolutionary process prevents an expedite analysis. By observation of Figure 11 and Figure 12, it is possible to conclude that these algorithms are quite susceptible to the initial parameters input in the beginning of the simulation and to the size of the solution space, even for a simple scenario as the one studied. Consequently, it is essential to perform several simulations in order to overcome this disadvantage, as well as considerations in minimizing the model complexity. In order to cope with these
restrictions, it is necessary to consider broad and rigid time and speed steps, which is not realistic taking into account the fact that the pumps can be operated at any given time and, in the case of VSD's, can operate at any desired speed. Thus, as demonstrated, a careful and critical analysis of the solutions obtained is indispensable to allow more efficient strategies.

From the manual override optimization process, satisfactory results were obtained when compared to the GA, given the fact that the criteria were primarily to avoid consumption in peak hours and to prevent volume variation in the tank. The solutions presented by the GA also complied with these criteria, with the advantage of reaching even more efficient scheduling strategies. Nevertheless, and only for simple systems as the one studied, the manual override approach requires the user to perform a limited number of hydraulic simulations and the iterative critical analysis of the results until an acceptable optimization, i.e. one which reaches a minimal cost and complies with the system constraints, is achieved. By contrast, the GA runs several thousand simulations in order to converge to a solution which might not be the most optimal, but it is indispensable to optimize more complex scenarios, such as the one with 2 pumps (pump interactions, additional pumps) or with a VSD (additional speed steps), which render a manual optimization unfeasible. Furthermore, it was demonstrated that given the stochastic and random nature of this algorithm, its usage requires careful considerations of all the variables involved, particularly regarding the solution space, in order to prevent results which are not optimal.

Although theoretically quite versatile, the VSD motors did not perform considerably better than the FSD motors in economic terms. It is reasonable to assume that these types of motors can present considerable advantages in systems with unpredictable or more disparate demands, as well as in situations where the total head is variable, which is not the present case. Also important is the fact that, although in this investigation the minimum speed was of 87% of its maximum, these motors allow speeds as low as 12%.

A secondary conclusion is the importance of carefully considering good practices in GA optimization. The results obtained by the 1 pump/6 scenario are the most consistent ones when compared to the 2 pump/3, with little variation between solutions with different initial parameters, pointing to a systematic convergence towards an optimal solution. This demonstrates the importance of model complexity and solution space in obtaining the best possible results.

BIBLIOGRAPHY


GRUNDFOS – Pump Handbook, Management A/S Grundfos, 2004

KOLJONEN, J; ALANDER, J. T. - Effects of population size and relative elitism on optimization speed and reliability of genetic algorithms. Department of Electrical Engineering and Automation, University of Vaasa, Vaasa (Finland), 2006.


TSUTIYA, M. T. - Abastecimento de água. 2a edição. São Paulo (Brasil): Departamento de Engenharia Hidráulica e Sanitária da USP, 2004, p. 10

WHITTLEY, D. – A genetic algorithm tutorial. Computer Science Department of the Colorado State University, Fort Collins (USA), 1994, vol.4, no.2
