OPTIMIZATION OF PUMPING STATIONS IN COMPLEX WATER SUPPLY NETWORKS THROUGH EVOLUTIONARY COMPUTATION METHODS.

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Abstract

The proper scheduling of pumps operations in water supply systems yields to energy cost-savings. The pumps schedule is the set of many combinations of pumps operation parameters, variables in time, which must fulfil the system restrictions. Traditional approach to this problem leans on the man's experience, while in the last decades many optimization procedures have been developed.

In the paper, a method based on Genetic Algorithms to optimize the pumps functioning in water distribution networks is chosen and described. The purpose of the optimization is to reduce the energy consumption while maintaining a good service, considering the problems related to the calibration of a high number of parameters and many constraints.

The developed method is then applied to the water supply network of Milano, Italy, which is a large and complex system with no suspended reservoirs because the hydraulic head is maintained by the action of 31 pumping stations. On the basis of real data, and following a field survey, the operations of the entire network and its pumping stations, with the actual scheduling, are firstly simulated with a purpose-developed software which uses the Epanet Toolkit, and then optimized with the proposed method.

The results of the applied optimization procedures show that the new operational system produces a significant improvement and economic saving.

Keywords: water distribution, genetic algorithms, optimization, energy saving.

1. Introduction

Water distribution networks are crucial components of water supply systems. They are among the main infrastructure assets of a society, and their management must be effective, efficient and energy saving. The hydraulic head of large towns is very often completely maintained by the action of a number of pumping stations: in such systems a good management of the pumping station, in order to minimize the power consumption, is a critical aspect. To this end, hydraulic constraints are not sufficient to find the best system, which requires that economic and energy conditions be taken into account. In order to handle this kind of complex and multi-objective optimization problem Evolutionary Computation (EC) methods are often used. Because of the large number of parameters and the complexity of the system, the early methods based on linear or non-linear programming or, even worse, complete enumeration, are not applicable. Starting in the early Nineties, the different existing (meta)heuristics frameworks have been applied to solve the water supply networks related optimization problem. The taxonomy reported in De Corte and Sörensen (2012) divides metaheuristics frameworks into three classes: (*i*) *Local search metaheuristics*, which operate on a single complete solution and iteratively improve it by making small adjustments called moves; (*ii*) *Population-based metaheuristics* operate on a set of solutions and find better solutions by combining solutions from that set into new ones; (*iii*) *Constructive metaheuristics* build a solution by working with a single, unfinished, solution and adding one solution element at a time.

Genetic Algorithms (GA) (Goldberg 1989) methods, which belong to the “population based metaheuristics”, are often chosen. GA are a technique of Evolutionary Computation appropriate for combinatorial optimization (Eiben and Smith, 2003) and their use is central in modern water resources planning and management. They have been widely used in the past two decades to improve the efficiency of water distribution systems when traditional calculus-based and enumerative optimization methods have proved unable to deal with the geometrical complexity of those systems. One of the first water engineering applications of GA was related to the optimization of pump schedules for a serial pipeline (Golberg and Kuo, 1987; Simpson et al, 1994). GA have been also used for least-cost design (Savic and Walters, 1977); as mentioned, network optimization has also been studied, applying different methods (Schaake and Lai, 1969; Alperovits and Shamir, 1977; Fujiwara and Khang, 1990).

Mackle et al. (1996) were among the first to apply a binary GA to pump scheduling problems in order to minimize energy costs, subject to reservoir filling and emptying constraints. Savic and Walters (1997) developed a multi-objective GA (MOGA) approach to minimize both the energy costs and the number of pump switches, while Wu et al. (2009) directly computed the pump speed through the matrix system of a global gradient algorithm. The first industrial applications of GA to the pump scheduling problem are reported in (De Schaetzen et al., 1998; Illich and Simovic, 1998; Atkinson et al., 2000). Van Zyl et al. (2004) developed a hybrid optimization approach in order to reduce excessive running times. Further computational efficiency have been achieved by Rao and Salomons (2007) through their new approach for the real-time, near-optimal control of water-distribution networks through a process based on the combined use of an artificial neural network for predicting the consequences of different control settings and a genetic algorithm for selecting the best combination. Prasad and Park (2004) developed a multiobjective GA approach to the design of a water distribution network, the objectives considered were minimization of the network cost and maximization of a reliability measure. Shamir and Salomons (2008) used a reduced model of the network which reproduces its performance over time with high fidelity with optimization by a genetic algorithm. Costa et al. (2010) used GA for optimizing the water supply system operations in the city of Ourém (Portugal). Behandish and Wu (2013) applied a modified GA able to deal with integer parameters and ANN to predict the hydraulic state of water distribution.

Dealing with real networks is not a simple task, and this is probably the reason why Walski et al. (2010) stated “A great deal of research has been conducted on optimizing pumping operation but such optimization is still not widely used.” therefore a number of different solutions has been developed.

In this paper, GA have been selected as the Authors found (Becciu et al., 2014) that methods belonging to the “Local search metaheuristics” risk to be trapped in unfeasible spaces, while methods belonging to “Constructive metaheuristics” are promising but quite difficult to be calibrated and requires further research. Therefore, a simple GA is set out in order to improve the performance of the water distribution system in Milano (Italy) in terms of power consumption at pumping stations, trying to assess whether this method is appropriate to be used in the field. In Milano, as mentioned, similarly to most of large cities, there are no reservoirs and the hydraulic head is given by 26 pumping stations positioned quite uniformly all over the city.

Results show that significant improvements can be achieved in terms of savings of energy and, therefore, of money. Tests on a pumping station demonstrate that the results obtained are reliable. Finally, GA are metaheuristic methods that can be successfully applied to pumps optimization in complex systems; they have been shown to be stable and to bring to good results. Possible improvements are investigated and briefly described in the conclusions.

2. Optimization algorithm

The aim of the research was to find the best scheduling of pumps functioning, able to ensure the same level of service now guaranteed with the minimum energy expenditure. Water is presently distributed assuring that heads in all the nodes of the network are higher than 25 m. This is an optimization problem with constraints, and Genetic Algorithms technique is found to be appropriate among the Evolutionary Computing “dialects” (Eiben and Smith, 2003; Becciu et al., 2015).

The method is implemented in a purpose developed software, which uses the Epanet Toolkit to solve the network once a new scenario is defined.

The status of the pumps has been implemented in a binary string, where each pump is represented by 3 bits (i.e. $2^3 = 8$ possibilities) which describe its working status, i.e.: pump off, pump on working at 40, 50, 60, 70, 80, 90 and 100% of its nominal speed.

The objective function (O.F.) to be minimized is the power required by the system W (and consequently the required energy) which is obtained by summing the power required by each running pump:

$$O.F. = \mathrm{W} = \sum_{\mathrm{i}=1}^{\mathrm{N_{pump}}} \frac{\gamma \mathrm{HQ}}{\eta} \tag{1}$$

where γ is the specific weight of the fluid (water), H is the heads of the pumps for the discharge Q, and η is the efficiency of the pump; this O.F. is minimized every full hour.

The first step in the implementation of the GA is the generation of a number of configurations that are used as the first generation of solutions ("population"): one of these is the actual configuration, the others are created randomly by the software.

New populations are generated starting from the previous with the usual methods of cross-over and mutation (Goldberg, 1989; Eiben and Smith, 2003). Moreover, a 10% of elitism has been used in order not to lose the best individuals.

Each configuration (individual) is simulated using the Epanet Toolkit in order to evaluate the correspondent value of the objective function (i.e. its fitness), and to check the constrains. If the pressure at some control points falls below the above-mentioned value of 25 m, the value of the *O.F.* is increased in function of the difference from the acceptable (*MinPres*) and the computed (*CompPres*) pressures in order to penalize the configuration; the O.F. therefore becomes:

$$O.F. = W \cdot 5 \cdot \left(1 + \frac{MinPres - CompPres}{MinPres}\right) \qquad \text{when } CompPres < MinPres \qquad (2)$$

where W is defined with the eq. (1) and, as mentioned, *MinPres* = 25 m. Obviously, the penalty functions are not derived from theoretical consideration, but depend on the problem to be studied; in this case the function is studied in order to increase the required power of 20% per meter; moreover, a check on the respect of the condition $MinPres \geq 25\,m$ has been performed on all the carried out solutions, and it has been found that the "best" solutions satisfy this requirement.

Optimization is run hour by hour, so the daily optimization is given by the combination of hourly best results. Figure 1 shows the framework of the whole procedure. Because of the intrinsic randomness of the algorithm, each simulation may produce a different result; therefore, for every hour of the day 10 simulations were run with different starting points, i.e. different initial populations, composed by one individual equal to the actual configuration and the others randomly generated.

3. Case study: the Milano water supply network

The water supply system of Milano (Motta 1989) acquires drinking water from a number of wells, and pumps convey the discharge to reservoirs located at ground level. Water is pumped directly from those reservoirs into the network, without further reservoirs located at higher altitude being necessary. The hydraulic head is therefore generated by the pumping stations, the action of which balances the effects of water demand, as suspended reservoir are not present.

The pipelines have a total length of 2200 km. The network comprises 31 pumping stations (at the moment 26 are working and connected to the main network, and therefore inserted in the model), and a number of pumps (their number being in the range 3-5) are installed in each of them; each pump works with a discharge in the range 200-400 l/s and with a maximum head of 50 m. On the whole, 96 pumps are currently working connected to the main network. Most of the pumps work with a fixed engine speed, but some of them are equipped with Adjustable Speed Drive which enable pumps to work at different velocities. Currently, the network is managed with traditional and empirical techniques.

The first step of the study was building the model of the network in order to evaluate its behaviour and verify whether the knowledge about the system is sufficient for its adequate representation, if necessary through the calibration of the model itself. We are perfectly aware that it is simply not possible to represent such a network in all its details and therefore there will be always some model descriptions which can be judged as “rough” or “not adequate”. However, to show the potential of the applied model and to improve the efficiency of the studied system the representation adopted seemed to be appropriate.

The available data were the geometry (topology of the network, lengths, diameters, materials, etc.), the mean daily water demand, the pumping schedule for each station, the values of pressure and discharge downstream of each station and in some other junctions quite uniformly distributed within the network. Figure 2 presents a scheme of the whole network.

These data were used to build a simplified model of the water supply network using the well-known Epanet software. Simplifications consisted in the insertion in the model only of pipes with a diameter larger than 300 mm. This simplifications was necessary to reduce the time required to build the model and to perform the simulations. However, it was possible to produce a fairly accurate reconstruction of the network, which model is made of 4964 junctions, 96 pumps, and 26 stations, with an overall length of pipes equal to 460 km. As mentioned, five pumping stations have been neglected because not directly connected to the main system or not working.

The network was simulated for an average day using the daily average hourly demand curve with a time step of 5 minutes.

Figure 3 shows the comparison between simulation results and real data recorded in a pumping station (Baggio, positioned in the SW of the town) and at some points of the network equipped with appropriate instrumentation. As can be seen, the simulated pressures are, in most cases, above the recorded values, and this has been investigated with field tests.

4. Field tests

Some tests were performed at one of the pumping stations in the Milano network, in order to evaluate the performance of the real system and the robustness of the model. The station chosen, named Salemi, is located in the North of the town and it is equipped with four pumps, two with Adjustable Speed Drives and two without such devices. The curves of the pumps were reconstructed in order to be compared with the theoretical curves provided by the system manager and used as inputs to the Epanet model; the result was a good adaptation. Field tests also revealed that fixed speed pumps installed in the Milano water supply network are oversized, as can be seen in figure 4. When the speed of the pump is 100%, the working point is positioned somewhat “to the right” of the curve; the efficiency of the pumps falls dramatically and it is often below 60%. Only when the velocity is reduced the working point moves “to the left” and the efficiency increases. To avoid cavitation, the managers of the network have to partially close the valves positioned downstream the pumps, especially in the morning when the pumps are turned on quite early and their use is slowly requested by the users. These valves induce headlosses which rise power consumption. However, as can be seen in figure 4, the speed reduction which can be obtained with the Adjustable Speed Drives, increases the efficiency of the pumps.

The presence of such valves, not included in the model, explains the differences between recorded and simulated data. However, in the paper it has been decided not to insert those valves, as they are not good management of the system; moreover, in the model a fixed efficiency equal to 0.75 has been assigned, because lower values mean that the selected pumps are inappropriate for the system.

5. Results

The results revealed a weak relation between the population size and the number of iterations; generally speaking, the optimum is reached when the individuals are few tens only, while the required number of iterations is even smaller. In this job, the number of individuals has been set equal to 100, which is quite small, if compared with the number of the variables to be set (equal to the number of pumps, and therefore 96) while, applying the rule-of-thumb of a number of individuals equal to five times the number of parameters, convergence should be expected overcoming 500 individuals. However, in Table 1 results are reported for 7:00 a.m. and different numbers of individuals and iterations. As can be seen, the best result is improving when increasing the number of individuals, but that improvement is quite small (1.3% passing from 50 individuals to 100, and 2.8% passing from 100 individuals to 500). No improvements can be ascribed to the increasing of the number of iterations; this is applicable to all the other hours: Figure 5 shows the obtained power (W) trend for each configuration obtained through the simulations, carried out for 9:00 p.m. and, as can be seen, the value of W decreases, becoming steady after about 20 thousand runs, but with the minimum reached after only 1500 iterations that, for a population of 100 individuals, means 15 generations.

The fast convergence can be ascribed to the fact that the variables to be set (i.e. the velocity of pump functioning) are not continuous and they can assume only fixed (predetermined) values, and therefore the possible solutions fall in a limited field.

As mentioned, simulations have been performed considering the efficiency of the pumps is equal to 0.75, which is larger than the values computed for the actual pumps, but it has been used in order to have a more consistent comparison between the different scenarios and to carry out results which can be considered more general. For the case of Milano, the consequence is obviously that the expected benefits deriving from the installation of the Adjustable Speed Drivers and their optimization is greater than those computed.

Table 2 presents a summary of the results, considering the best configuration (individual) found for each hour of the day. As can be seen, it is possible to save up to 18.9% of energy (on average on one day) with fixed velocity pumps and up to 30.2% of that energy using Adjustable Speed Drivers.

In particular, the simulations performed using Adjustable Speed Drivers show that a significant improvement is possible: the minimum saving is 17.1% (at 5:00 a.m.) and the maximum is 38.8% (at 10:00 p.m.). Meanwhile, improvements related to the system without these devices have a minimum of 7.6% (at 8:00 a.m.) and a maximum of 29.2% (at 2:00 a.m.).

Moreover, to be noted is that in all cases the speed of the pumps never decrease below 70%, because below that value the head of the pump is not sufficient to provide discharge to the network. The required power over the day is summarized in figure 6 for the actual case and for the two optimizations (with and without the Adjustable Speed Drivers).

Finally, in order to gain an idea of the possible economic savings, the energy cost is set equal to 0.10 €/kWh for the entire day. Therefore, considering the actual total energy in a year equal to 38,200,000 kWh, without Adjustable Speed Drivers it is possible to save up to 6,840,000 kWh/year, which means an economic saving of the order of 684,000 €; with the use of those devices it is possible to save up to 11,627,000 kWh/year, which means an economic saving of 1,162,700 €.

6. Conclusions

The paper described the application of Genetic Algorithms to optimize the functioning of the pumping stations of the city of Milano (Italy).

To this end, the model of the water supply network was implemented in the well-known Epanet software, and the results of the simulations were checked against real data.

Thereafter, thousands of different pumping configurations were tested by means of a simple Genetic Algorithm in order to find the best configuration, i.e. the configuration able to guarantee the same today service and the best energy savings. The configurations were tested with and without the use of Adjustable Speed Drivers. The results showed that a dramatic improvement is possible, both with and without the use of these devices.

The results may require further refinement owing to the simplifications adopted for the model, but they are nevertheless encouraging because of the savings that can be achieved in terms of both energy and costs.

Field tests showed that the pumps installed in the Milano stations are probably oversized, and therefore the above mentioned values can be increased with a more appropriate choice of the pumps.

So far, GA have proved to be an appropriate method for optimization purposes, with many parameters involved and with constraints. As well known, these methods do not allow to find the “best” solution, but a solution which is close to the maximum. Therefore, although good results have been achieved, refinements might be required to further improve the solution. Moreover, methods based on “constructive metaheuristics”, as PSO which has been found promising in Becciu et al. (2015), should be tested to take advantage of their capabilities.

Moreover, further research is necessary to combine the energy savings with the different requirements of a complex network like Milano’s, which targets might be contradictory and therefore it may be required to move on the Pareto boundary.

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Individuals	50	100	500	500
Iterations	100	100	100	500
# Run	Power	Power	Power	Power
1	318404	315949	314083	311146
2	319605	315641	307342	***304444***
3	317896	315597	307875	313530
4	316469	316574	309452	312418
5	319605	313486	310333	310123
6	319605	312243	310139	311367
7	319605	315640	312134	308330
8	317871	316469	307748	313426
9	***315641***	***311533***	309895	304454
10	316080	312473	***302695***	312189

Table 1: Energy required: results of the simulations for 7 a.m. with different GA parameters.

Hours	0	1	2	3	4	5	6	7	8	9	10	11
% savings fixed speed	17.1	23.3	29.2	28.3	24.2	12.5	11.1	16.4	7.6	9.5	11.5	17.5
% savings adjustable speed	30.0	36.8	36.3	33.0	28.7	17.1	20.2	18.8	26.8	26.1	37.8	31.4
Hours	12	13	14	15	16	17	18	19	20	21	22	23
% savings fixed speed	18.5	21.8	17.1	19.1	19.0	21.2	18.8	22.2	20.4	18.3	21.3	27.4
% savings adjustable speed	32.8	30.1	33.1	34.8	37.4	28.0	24.8	29.2	28.3	34.7	38.8	30.6

Table 2: Energy saved, in percentages, with and without the use of inverters for each hour of the average day.