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Near real time pump optimization and pressure management

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Abstract

Management of existing systems can be interpreted as sets of decisions to make regarding pumps and valves to create hydraulic conditions able to satisfy the demand without operational problems such as pressures lower or higher than the normative pressure values. However, among the large number of combinations, some of them manage to reduce energy consumption, by finding the best operating point for pumps, and also water losses, by finding the best operating point for pressure reducing valves (PRV). Several works may be found in the literature using recent and advanced optimization techniques to define pump and valve operation. However, the processing time to define operational rules is a limiting factor for real time decision-making. Taking into account the need to improve the models in terms of optimal rules to apply in near real-time operations, this work presents a hybrid model (simulator + optimizer) to find pump speeds and PRV set points, aiming at combining energy savings with pressure control while reducing water losses. PSO is applied as the main optimization algorithm, which can also work in cooperation with other bio-inspired concepts to deploy an effective and fast search algorithm. The results allow comparisons with other techniques and show the ability of PSO to find an optimal point of operation

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1. Introduction

The challenge of urban development for this century is bringing environmental resources savings and availability to serve citizens with quality. In this way, the smart city concept appears as a way to manage urban systems with high technology. A smart water system may be characterized by the way the system is managed following the well-known Smart City paradigm [1]. This paradigm, given a water system, implies that the companies operate the system using the available technology to reduce energy consumption and water losses, while respecting consumers' needs. Usually, the operation of water distribution systems (WDSs) is based on the expertise of operators to manage valves and pumps to guarantee the supply safely and as efficiently as possible.

The costs associated with water pumping stations in WDSs are the most significant for the water supply companies, according to [2]. Following the current tendency, some important studies have been developed in an effort to find a better approach of the energy consumption problem. Water management problems have been treated successfully with the application of optimization techniques [3] and the definition of pump schedules during a determined period of time, usually 24 hours. The use of various bio-inspired algorithms is the most important approach for energy saving in WDSs, as can be inferred from [4, 5, 6, 7], for example.

Bio-inspired algorithms have been widely applied to water management problems, especially due to their easy integration with hydraulic models, which allows estimating energy consumption and hydraulic state of the network during a specific period. [4] apply Ant Colony optimization (ACO) to determine the hourly schedule of pump operation for 24 hours by switching pumps statuses (on/off). The authors consider damage risks for the pumps and limit the number of switches to three. [5] present a modified classical optimization variant for pump schedule, using hybrid linear programming linked to a greedy algorithm to find the optimal schedule for pumps. The method is compared with GAs to show high efficiency while maintaining the accuracy when applied to various benchmark networks.

Considering the possible damage for pumps associated to the status switch approach for optimal pumping schedule, and taking into account the management improvement when variable-speed drive (VSD) is used, [6] propose the use of Particle Swarm optimization (PSO) to define the best speed of pumps aiming the near-lowest energy cost for 24 hours. This approach allows better long term management, once the pump station is protected. However it requires the installation of VSD. The use of hydraulic simulators coupled with optimization algorithms requires high performance capabilities to solve the pumping problem because the objective function, usually defined to consider energy cost, has to be calculated, thus increasing the processing time.

Getting rid of the simulation need, [7] apply a meta-modelling technique with artificial neural networks (ANNs) trained under several scenarios to define the hydraulic state of the water distribution network. For the energy saving problem, the meta-model is coupled with a GA algorithm to define pump status and tank operation. The authors show a daily cost reduction of 15% when applied to a real network in UK.

In addition to the energy costs, water losses have been widely studied as a way to improve the global efficiency of water systems. Management of pressure through control valves, mainly by PRV, is the flagship strategy used by water utilities. In this way, the determination of the optimal set point for PRVs is an optimization problem for which several researchers have proposed solutions. [8] highlight the susceptibility of aged and high pressures zones for leakage occurrences in water networks. The authors present an integrated model to define optimally the number, position and set point of PRVs aiming to water loss reduction. A model of extended period simulation (EPS) coupled with GA optimization is applied to find the optimal solution.

Taking into account water losses reduction, [9] propose an alternative hydraulic network model for PRVs coupled with non-linear optimization algorithms to find the best operational set point of valves. The importance of water loss reduction is strictly linked with economic and environmental challenges imposed by climate change and growth of cities. [10] present a multi-objective optimization process based on GAs to solve the location and set point determination problems to reduce water losses. The main advantage of this work is the reduction of the space search for the location problem through energy dissipation evaluation for the pipes.

Even though several studies have been developed to reduce energy costs in pump operation and water loses, real-time approaches have gained importance in this research field recently. One of the pioneers in real-time control for WDSs is [11], which presents a real-time optimal operation model aiming at cost reduction, meeting the required demands at minimal pressure. Water demand is updated hourly, allowing a new adjustment of pump statuses. The model relies on a SCADA system, responsible to update tank levels and the hydraulic status of the network. Considering the importance of model validation, [12] apply the real-time operational model proposed by [11] using a reduced model for 24 hours as an operational horizon. The authors report an energy saving of 8 and 10% for summer and winter simulation, respectively.

The near real-time approach requires a previous stage to determine correctly accurate manoeuvres, corresponding to water demand forecasting. [13] use an ANN-based algorithm coupled with a multi-objective GA model to determine optimal operation of pumps in real time. A real WDS from Araraquara, Brazil, is optimized achieving a reduction of 13% in energy consumption. [14] present an approach with three coupled models to define in real time the pump optimal status. The operation of the real, medium-size water distribution network of Seoul, South Korea, is defined and compared with a standard operation. The energy saving found with this approach is in the range of 19% to 27%.

Several works have been developed to find the best operational scenario for pumps in real time, resulting in high performance of optimizer models and demand forecasters. Furthermore, the attention of pressure management increases, consequently increasing the works which propose optimal operation of PRVs as an option for water losses control. Furthermore, the status switch of a pump as a decisional variable type for pumping schedule optimization limits the possibility to improve energy saving, since the number of switches has to be limited to avoid maintenance problems. The use of VSD can be an alternative for pump operation, allowing pump status shifts using the relative speed as a decision variable. Another important point of real-time control overview is the possibility to find, for each time step, the best set point of valves, thus guarantying the best pressure management at all times.

In this way, we propose near real-time pumping schedule and pressure management optimization. Applying this combination for a horizon of 24 hours, the water demand is forecasted each hour using an Adaptive Fourier Series. Considering this demand, an optimization model coupled with a hydraulic network simulation searches for the best pump speed and optimal set point of a previous placed PRV.

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2. Adaptive Fourier Series for water demand forecasting

Social behaviour is the main component that defines the variation of water demand consumption during the day. In this sense, a historical demand analysis shows a near periodical oscillation, as shown by [15]. Taking this into account, discrete Fourier series can be an interesting tool to develop a forecasting model. The formulation presented by [15] was proposed by [16], which uses a Fourier trigonometric adjustment as a way to tune non-regularly spaced points. Normalizing the points to the interval [0, 2π], equally spaced by (1), the regression function (2) can be written as (2).

$$t_i = \frac{2.\pi.i}{N}, \tag{1}$$

$$f(t_i) = d_i^* = a_0 + \sum_{j=1}^{M} (a_j.cos(j.t_i) + b_j.sen(j.t_i)). \tag{2}$$

Here, t_i is the i-th normalized time point, *N* is the total measurement points, $f(t_i)$ is the approximated function value, in this case corresponding to d_i^* the water demand forecasted, by the Fourier Series with *M* terms, where a_j and b_j are the adjustable coefficients of the series.

Taking d_i as the real demand, an error e_i should be calculated from the difference between the real demand and the predicted demand by (2)

$$e_i = \left(d_i - a_0 - \sum_{j=1}^{M}(a_j.cos(j.t_i) + b_j.sen(j.t_i))\right)^2. \tag{3}$$

One way to find each coefficient of equation (5) is the application of the Least Square Method that results in:

$$a_0 = \frac{\sum_{i=1}^{N} d_i}{N}, \tag{4}$$

$$a_j = 2.\frac{\sum_{i=1}^{N} d_i.cos(j.x_i)}{N}, \tag{5}$$

$$b_j = 2.\frac{\sum_{i=1}^{N} d_i.sin(j.x_i)}{N}. \tag{6}$$

Even if the approximation of water demand using Fourier Series has a good accuracy, the error increases as the forecasted value is far from the used point values. To reduce this error, the adjustable coefficients are updated at each time step, using the water demand measured at the last time and moving the data window forward, as shown in Fig 1.

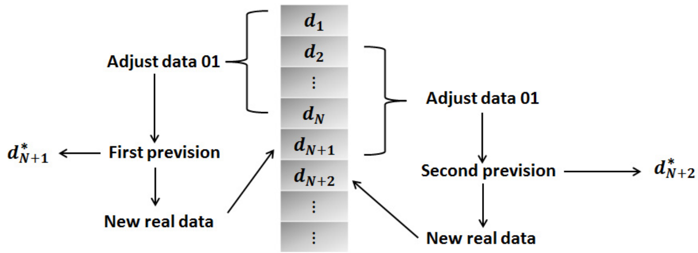


Fig. 1. Real-time updating process of parameters, adapted from [17]

3. Optimization problem

The optimal operation problem in real time has the main objective to minimize the costs linked with operation. Pump energy consumption and water loss should be reduced through optimal pump speed and pressure set point for PRVs. The energy consumption, named here energy objective function (OF_e) during a 24-hour horizon may be written as:

$$OF_e = \sum_{t=1}^{24}\sum_{p=1}^{N_p} \frac{\gamma.Q_p(\alpha).H_p(\alpha)}{\eta(\alpha)}.t.c_t, \tag{7}$$

where t is the time step when pump p delivers a flowrate $Q_p(\alpha)$, working with a relative speed α for a hydraulic head H_p with efficiency η. The energy cost is usually linked with the time of the day and is represented by c_t in a network with N_p pumps.

The water loss cost should be estimated through the evaluation of water leaks and the associated cost of water. However, depending of the energy consumption, the water loss cost can be very small, thus hampering the optimization process. An alternative to treat the pressure management without an estimative of water losses cost, a usually equating is the relative difference between minimal operation pressure (P_{min}) required by the system and the real operation pressure, termed here as pressure objective function (OF_p), as shown by (8):

$$OF_p = \sum_{t=1}^{24}\sum_{n=1}^{N_n} \frac{|P_{t,n} - P_{min}|}{P_{min}}, \tag{8}$$

where $P_{t,n}$ is the pressure at node n in the time step t in a network with N_n demand nodes.

As can be noticed, while (8) is a non-dimensional function, (7) is the energy cost, in monetary units. To bring both functions to non-dimensional representation, equation (7) can be divided by the maximal value of energy cost that is found using $\alpha = 1$, the nominal speed of the pump. Finally, the objective function is written as (9).

$$OF = \sum_{t=1}^{24} \sum_{n=1}^{N_n} \frac{|P_{t,n} - P_{min}|}{P_{min}} + \frac{\sum_{t=1}^{24} \sum_{p=1}^{N_p} \frac{\gamma . Q_p(\alpha) . H_p(\alpha)}{\eta(\alpha)} . t . c_t}{En_{max}}. \tag{9}$$

Considering the operation constraints, standard pressures (P_{min} and P_{max}) and tank levels ($L_{T,min}$ and $L_{T,max}$) should be taken into account to find the operational schedule that delivers the forecasted demand safely. Furthermore, the minimal speed should be defined, to avoid noises and maintenance problems at pumps [18]. Thus, the optimization problem is subjected to:

$$P_{min} \leq P_{t,n} \leq P_{max}, \tag{10}$$

$$L_{T,min} \leq L_{t,T} \leq L_{T,max}, \tag{11}$$

$$\alpha \geq 0.5. \tag{12}$$

The optimal solution is found by applying PSO, and the hydraulic state of the network is determined using the hydraulic simulator EPANET toolkit version for Matlab developed by [18]. However, as most bio-inspired algorithms, the PSO original version only does unconstrained search, which requires a special treatment of constrains through a penalty function. Using the generic formulation proposed by [19], the penalty function can be written as (13).

$$Pen = \sum_{i=1}^{N_c} \beta_i . |x_i^s - x_i^{lim}|^k, \tag{13}$$

where Pen is the total penalty value for a solution of the problem with N_c constrains, which is represented by x_i^{lim}. β_i and k are the calibrated parameters to favour convergence. Finally, the compound objective function (COF) is written as:

$$COF = OF + Pen. \tag{14}$$

4. Particle Swarm Optimization

Bio-inspired algorithms are applied in many research fields, mainly because their easy implementation and power to find near optimal solutions without calculation of the Jacobian and/or Hessian matrices. GAs, PSO and Simulated Annealing (SA) have been the most important bio-inspired algorithms applied to several hydraulic problems such as optimal design [20], optimal pump operation [21], model calibration [22] and optimal PRV placement and set point definition [23]. Comparing these three algorithms, two outstanding points of PSO may be noticed: fast convergence, mainly compared with SA, and low number of parameters that must be defined by the user, when compared with GA. In this sense, this work uses the original method proposed by [24] to solve the real time scheduling problem.

The PSO is compound by a set of particles which have two associated vectors: position and velocity. Usually, each vector starts randomly inside a defined range. The position vector is interpreted as a solution of the problem and allows the objective function evaluation. Then position and velocity are updated, according to the following equations:

$$x_s^{t+1} = x_s^t + v_s^{t+1} , \tag{15}$$

$$v_s^{t+1} = w^t . v_s^t + c_1 . r_1 |l_b^t - x_s^t| + c_2 . r_2 |g_b^t - x_s^t| , \tag{16}$$

where x_s^{t+1} is the position of particle s at iteration $t + 1$, updated using the velocity v_s^{t+1}. The update of velocity is a combination of the last velocity value, weighted by the inertia parameter w^t, to avoid excessive particle roaming;

the difference between the best position of the particle s, l_b^t, and the actual position weighed by the cognitive parameter c_1; and, finally, the difference between the best position of the particle and the position of the swarm leader, g_b^t, weighed by the social parameter c_2. The random numbers r_1 and r_2 working as particle scatterers avoid premature convergence at local optimal points. The last two summing elements in (16) are responsible for the convergence of the method because they attract particles to the best point founded by the swarm.

Despite initial values for the particle vectors are usually selected randomly, the convergence time can be reduced when previous knowledge of the search space is added to the optimization problem. In this way, in this work we propose that 5% of the swarm particles start with a previous solution of the general problem. To find this first solution, taking into account the water demand time series available, we define a standard water demand pattern and solve the optimization problem finding the pump schedules and valve set points for each hour in a day. This solution is used to generate the initial position of the 5% selected particles. Fig. 02 shows the initial assembling vectors.

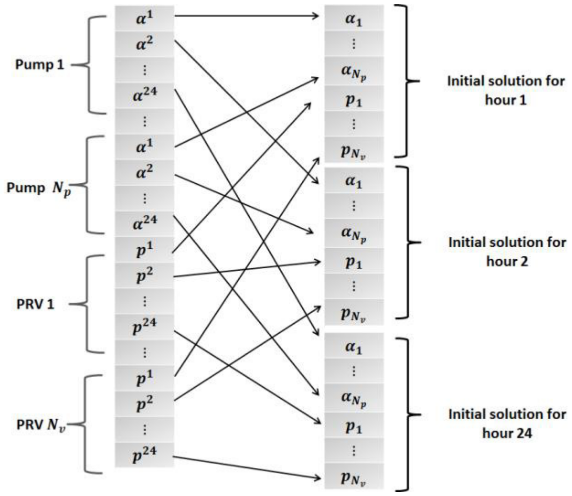


Fig. 2. Assembling of initial solution for each hour of day using previous solution obtained with extended period simulation

The advantage of this initialization is twofold: with the obtained previous solution convergence time is reduced; also, a large number of particles using this initialization will spare exploration of the search space. The limitation of 5% of particles to be initialized this way can guarantee high exploration to the potential solutions.

5. Results and discussion

This is study is developed on an adaptation of a real water network, Campos Do Conde II, located in Piracicaba, Brazil. This is a residential district measured area (DMA), with 121nodes, 153 pipes, 1 reservoir, 1 pump, 1 tank and 1 PRV. Fig. 03 presents the topology with node elevation developed with EPANET2.0. It is possible to observe a large nodal elevation difference between the highest and the lowest nodes. This difference propitiates the generation of a high pressure zone, isolated by a PRV to meet the system complying Brazilian technical standard about WDSs that determines the minimum dynamic pressure as 10m and the maximum static pressure as 50m. Some adaptations of the real topology are applied to the network to improve the presence of a pump, allowing the development of this work with a real network. The reservoir is placed at elevation of 625m and the pump at elevation of 616m. The pump is responsible to deliver the water demand at nodes with elevation higher than 630m. The price of energy is defined as 1 monetary unit (MU).

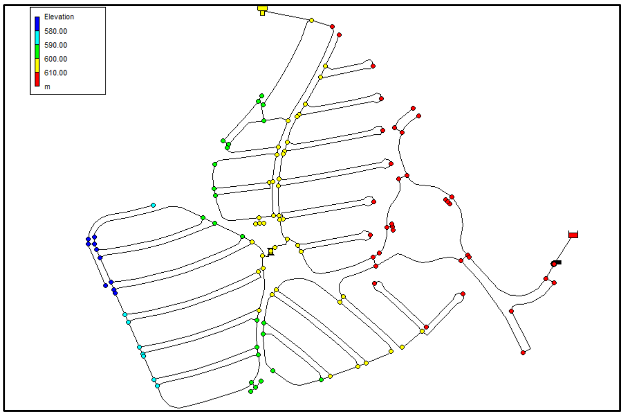


Fig. 3. Topology and nodal elevation of the DMA used as case study

In a first stage, the operational optimization is applied under a mean demand pattern that is determined using the time series of DMA consumption, as in Fig. 04. This is a usual approach to find pump schedule, and can result in interesting strategic rules. However, it is not able to take the pump all the time to its best efficiency point, which will increase the energy consumption of the system. PSO is applied on the extended period simulation using 50 particles initialized randomly. Once finished the first optimization process, the real time schedule definition starts using the Adaptive Fourier Series to define the demand for the next hour. The final water demand forecasting results for the 24 hours is shown in Fig. 04, which present the measured water demand for this day. The mean square error (MSE) between forecasted and the measured water demand is 0.0783l/s, corresponding to a correlation coefficient (R^2) equal to 0.991.

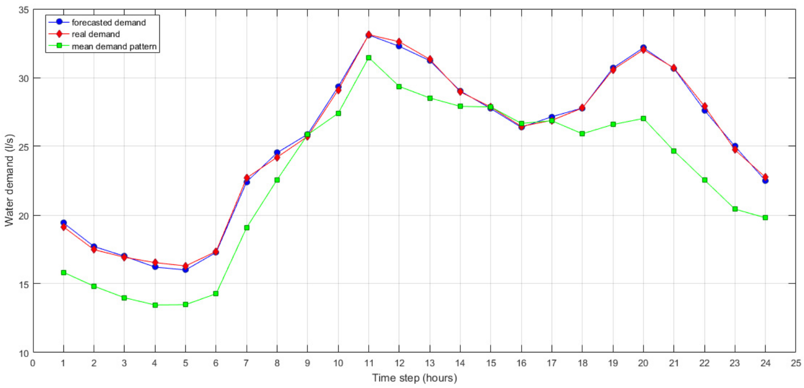


Fig. 4. Water demand forecasting compared with real demand and mean demand pattern

The difference between forecasted water demand and mean demand pattern confirms the possibility to improve the operation of the system, once the forecasted demand in lower than mean demand pattern. A comparison between the pump and valve rules for the mean and the forecasted scenarios evidences the reduction of the pump speed, shown in Fig. 05, as expected when the water demand is analyzed because the initial solution is obtained taking into account the green water demand pattern that is larger than the real one. Comparing the energy consumption of the system using the pump working at full speed and the pump working with optimal schedule, a saving of 54.62% of energy is observed. Furthermore, comparing the system using the pump working with the initial solution and the best solution, it is possible to reduce the energy consumption in an additional 12.40%. The control of PVR is found with the first solution, and an attempt to improve it is observed, mainly at the fifth hour, that caused the numerical deviation at this hour.

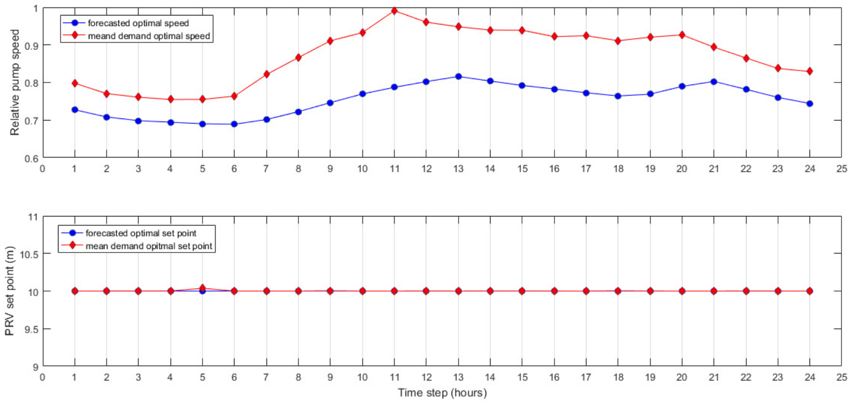


Fig. 5. Comparison between optimal control at real time and using mean demand pattern.

The water leakage, $Q_{L,n}$, linked to a nodal pressure P_n , responsible for the main portion of water losses at WDS, can be evaluated using the hydraulic orifice equation according to [25], as shown in (17),

$$Q_{L,n} = K.\sqrt{P_n}\,, \tag{17}$$

where K is a constant related to the orifice features.

Considering the difficult to define the parameter K, a relative leakage level can be defined, comparing the new scenario of nodal pressure, $P_{n,opt}$, and the default scenario $P_{n,full}$ as in (18). This comparison allows eliminating parameter K and, eventually, the total leakage Q_L only depends on the pressure difference (19).

$$Q_L = \sum_{n=1}^{N_n}\left(\frac{K_n\cdot\sqrt{P_{n,full}}-K_n\cdot\sqrt{P_{n,opt}}}{K_n\cdot\sqrt{P_{n,full}}}\right), \tag{18}$$

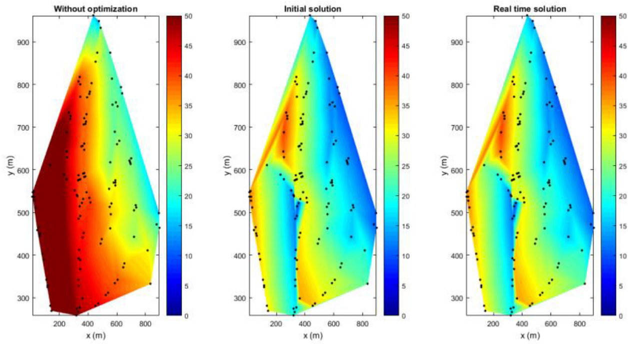
$$Q_L = \sum_{n=1}^{N_n}\left(\frac{\sqrt{P_{n,full}}-\sqrt{P_{n,opt}}}{\sqrt{P_{n,full}}}\right). \tag{19}$$

The scenario with initial schedule gets a relative leakage reduction of 37.67% while the scenario using the real time schedule reaches to 40.82%. Comparing the real-time solution with other solutions, it is possible to highlight the efficiency of the valve control observed in Fig (06-a), which shows the pressure surface for the maximal demand at hour 11a.m. In this case, the difference of the average pressure and the real-time solution is not significant, since the demands at both are similar. The efficiency of pump speed reduction for pressure control is more evident in Fig (06-b), which shows the pressure surface for the minimal demand at 5a.m. In this case, the reduction of pump speed increases the region with low pressure.

6. Conclusions

With the growth of the cities, the optimum management of WDSs becomes a way to allow universal access to drinkable water for citizens. The reduction of costs and the greenhouse gas emissions are important factors to be considered in WDS rule decisions to face such environmental challenges. The use of hydraulic simulations coupled with optimization algorithms has shown to be powerful enough to determine optimal operations. However, a mean demand pattern is not able to guarantee high efficiency of the system, since the change of the water demand during a day requires suitable adjustments of pumps' speed and/or PRVs' set points.

a)



b)

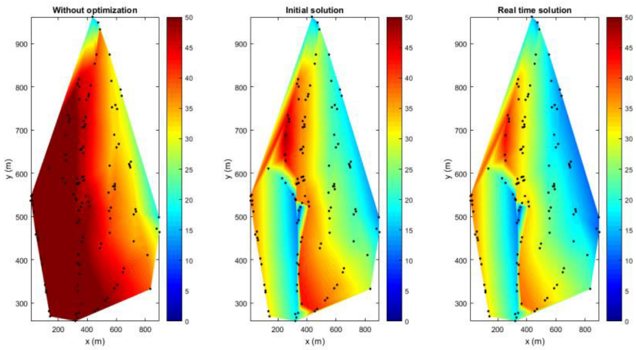


Fig. 6. Comparison of pressure at critical node according to the optimization approach for hour of maximum (a) and minimum (b) demand

A simple water demand forecasting model is applied here to determine the future demand, which updates the hydraulic model and allows the determination of the best speed of pumps and set point of valves to reduce energy cost and water leakage. An adaptive Fourier approach presents high accuracy and is very agile to find the future demand. These features are important in real-time approaches because the model cannot spend more time than the time step to define new rules. In this sense, also the use of an adequate initial solution is a way to save time in an hourly optimization that performs 1820 objective function evaluations per hour, corresponding to 16 minutes of processing.

The comparison among three scenarios: pump working at full speed and valve with no control, pump and valve working with optimal values found with mean demand pattern and, finally, pump and valve optimized in real time, shows the advantage of the application of the presented water demand forecasting model not only aiming at reducing energy cost but also at allowing better pressure management, eventually reducing water loss. As future works, the authors recommend the evaluation of the impacts of the error at water demand forecasting in operation, mainly at nodal pressure, to guarantee all the time the security of water supply.

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