# Optimal pump scheduling in water systems using multi-objective and multi-criteria analysis

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**Abstract**
Optimal control of pumps in water distribution systems is one of the most important ways to bring energy efficiency into water supply. This work presents a combined approach of multi-objective optimization and multi-criteria analysis to find, respectively, optimal solutions for pump control, and to automatically select non-dominated specific solutions from the Pareto front. The Non-Dominated Sorting Genetic Algorithm is proposed to solve the multi-objective problem, while the Analytic Hierarchy Process and the Technique for Order of Preference by Similarity to Ideal Solution are used to first get the vector of criteria weights and then achieve a Pareto solution ranking. Various scenarios of demand and leakage are addressed on the D-town network, allowing to evaluate the suitability of the approach to near-real problems. Potential future developments of the present research are also highlighted by discussing the usefulness of clustering alternatives to evaluate the goodness of each solution under the considered evaluation criteria.

**Keywords**: water distribution systems, optimal pump scheduling, multi-objective optimization, multi-criteria analysis.

## 1. Introduction

Operation of water distribution networks (WDNs) encompasses various manoeuvres of pumps and valves. Safe and efficient control can lead to the reduction of energy consumption in pump stations, responsible for a significant energy consumption, and to efficient control of pressures, thus reducing leaks. Despite operators' expertise may help find practical control strategies, a suitable hydraulic model linked to adequate optimization algorithms can improve control, thus finding a reasonable trade-off between security and economy.

The literature presents works using linear programming (Jowitt & Xu 1990), dynamic programming (Jowitt & Germanopoulos 1992), and evolutionary algorithms, such as Genetic Algorithms (Farmani *et al.* 2007). Non-linearity and discontinuity of the hydraulic problem turns the application of derivative-dependent methods almost impossible. Furthermore, with the increase of computational capacity and the huge availability of data, real-time optimal control has also been exploited, by linking optimization processes based on bio-inspired algorithms to water demand forecasting algorithms (Meirelles *et al.* 2017).

Frequently, single-objective approaches are used to find the minimal energy cost through the use of meta-heuristic algorithms. Derivative-free methods are useful for practical and real applications; however, they require special attention to the constraints. Since the operational problem must satisfy physical limits, such as minimal and maximal pressure along the network, unconstrained algorithms lead to the use of penalty functions, which artificially increase the value of the objective function when constraints are violated. Depending on the penalty function used, the search space can be abruptly modified and local minima may appear that turn the search process even harder (Brentan *et al.* 2018).

The problem of optimal control considers bounds for pressure, tank levels and switches of pumps' statuses, avoiding excessive start-stop cycles of pump stations. Another crucial element for real networks should be present in the simulation: leakage. Hydraulic simulations considering scenarios of leakage can help water utilities devise optimal control for pumps.

As an alternative to single-objective algorithms, various bio-inspired multi-objective algorithms (MOAs) have gained popularity within the water resources field (Montalvo *et al.* 2014, Odan *et al.* 2015). For MOAs constraints are handled as objectives to be reached. However, instead of a single solution, a MOA approach produces a full set of non-dominated solutions, integrating the so-called Pareto front, which water utility staff may use as an aid in decision-making. The application of MOAs for pump scheduling can provide the operators with various control scenarios. In contrast to the benefits for decision makers of having a whole set of scenarios, the number of Pareto solutions can increase significantly, depending on the number of objectives.

A large number of solutions turns the decision hard. Thus, we propose to manage the solutions obtained from the multi-objective optimization process with a suitable multi-criteria decision-making (MCDM) approach capable to rank the Pareto front solutions according to several weighted criteria.

The literature (Hamdan & Cheaitou 2017, Hadas & Nahum 2016) encourages the use of MCDM methods for various decision-making actions, and several techniques can be applied for ranking purposes (Cruz-Reyes *et al.* 2017). Among them, the most commonly used (Ho 2008) is the Analytic Hierarchy Process (AHP), originally developed by Saaty (1980), which calculates criteria priority vectors and rank alternatives. AHP is applied in the field of water management (Aşchilean *et al.* 2017) and, in general, in environmental applications (Lolli *et al.* 2017). Moreover, the literature (Zak & Kruszynski 2015, Zaidan *et al.* 2015) supports the integration of the AHP with other MCDM techniques to make final results more trustworthy.

The idea in this paper consists in using AHP for weighting evaluation criteria relevant to the decision-making process under study, and then evaluating the solutions based on those criteria. When dealing with a huge number of options, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), first proposed by Hwang and Yoon (1981) and then further developed in (Hwang *et al.* 1993), represents a flexible way to achieve their ranking.

As a further development of a previous research (Carpitella *et al.* 2018a), this paper proposes a revised combined approach of the mentioned perspectives. We aim to aid decision-making by first finding the Pareto front under leakage scenarios. The D-town network is used to test the impact of leakage on control decisions. A base scenario without leakage is used to compare the impact leakage has on various district metered area. Each scenario is then evaluated in terms of operational cost, operation lack of service, pressure uniformity and resilience. The NSGA-II is applied to find the Pareto front. Then the solutions are ranked (Kurek & Ostfeld, 2013) through TOPSIS, using criteria weights calculated with AHP. This points to those alternatives that present the best trade-off according to various aspects herein considered of primary importance.

## 2. Multi-objective optimization and multi-criteria analysis

### 2.1 Optimal pump scheduling

Consumption patterns are diverse and vary in different ways. Water demand dynamics, despite the presence of tanks in WDNs, turn the operation of pumps a complex decision problem. To tackle this problem, mathematical optimization algorithms are applied to schedule pump stations. The main objective is finding the best combination of pumps statuses guaranteeing safe operation, while using a minimum amount of energy. The optimization problem may be stated in terms of the energy cost, $F_1$, for the pump system

$$F_1 = \sum_{i=1}^{N_p} \sum_{t=1}^{P_e} \frac{Q(\alpha_{i,t}) H(\alpha_{i,t}) \gamma}{\eta_{i,t}} \Delta t c_t, \tag{1}$$

where $N_p$ = number of pumps working during time horizon $P_e$; $Q(\alpha_{i,t})$ = pumped flow and $H(\alpha_{i,t})$ = hydraulic head for pump $i$ operated under status $\alpha$ at time step $t$, with efficiency $\eta_{i,t}$. Finally, $\gamma$ is the specific weight of water, $\Delta t$ the time step, one hour in this work, and $c_t$ = energy cost at time step $t$.

Since pump control must deal with physical and operational constrains, the mathematical problem also considers: minimum pressure $P_{min}$ in the system; oscillation of tank levels between their bounds, $T_{k,max}$ and $T_{k,min}$; and the number of pump status switches during the operational horizon. To avoid penalty functions, objectives $F_2$, $F_3$ and $F_4$, respectively, integrate the multi-objective optimization process:

$$F_2 = \sum_{i=1}^{N_n} \sum_{t=1}^{P_e} \left| P_{j,t} - P_{min} \right|, \tag{2}$$

$$F_3 = \sum_{i=1}^{N_t} \sum_{t=1}^{P_e} \left| T_{k,t} - T_{k,min} \right| + \sum_{i=1}^{N_t} \sum_{t=1}^{P_e} \left| T_{k,t} - T_{k,max} \right|, \tag{3}$$

$$F_4 = \sum_{i=1}^{N_p} \sum_{l=1}^{P_e} s_{i,t}, \tag{4}$$

where, for a water network having $N_n$ demand nodes and $N_t$ tanks, $P_{j,t}$ is the pressure at demand node $j$, $T_{k,t}$ the water level in tank $k$, and $s_{i,t}$ the number of status switches for pump $i$ during the time horizon.

## 2.2 Non-dominated sorting genetic algorithms - NSGA-II

As for other water system problems, such as optimal design (Montalvo *et al.* 2014) or sensor placement (Ostfeld *et al.* 2008), pump operation problems (Ostfeld *et al.* 2008) also have conflicting objectives. The optimization of just one, such as the cost, cannot guarantee an optimal real solution. A robust MOA will turn these objectives compatible.

Based on classical genetic algorithms developed for single-objective problems, the NSGA-II is a development proposed in (Ancău & Caizar 2010). NSGA-II improves computation effort, elitism, and allows user-adjustment parameters.

In each iteration, NSGA-II improves the fitness of a population of candidate solutions to a Pareto front according to various objective functions. Through evolutionary strategies (e.g. crossover, mutation and elitism), the population is organized by Pareto dominance. Similarly, sub-groups on the Pareto front are suitable evaluated, what eventually promotes a diverse front of non-dominated solutions.

## 2.3 The AHP to establish criteria weights

The AHP is a helpful tool to drive subjective judgment towards effective solutions for decision-making problems, since it provides weights expressing the mutual importance of the elements considered in the analysis. The method is based on the construction of a hierarchical structure for representing goal, criteria and alternatives of the analysed decision-making problem through different levels.

Elements belonging to the same level of the structure are pairwise compared with relation to the elements belonging to the upper level by collecting expert judgment. Judgments are expressed and numerically translated according to the linguistic scale proposed by Saaty (1977) to fill in so-called pairwise comparison matrices (PCMs). The purpose is to calculate a vector of weights reflecting the grade of importance of a specific element with respect to the others.

In AHP, judgment consistency is crucial, and a certain degree of inconsistency is allowed when elucidating judgment (Carpitella *et al.* 2018b), since human reasoning cannot be fully consistent. Consistency is evaluated through the consistency ratio $CR$ (Saaty, 1977):

$$CR = \frac{CI}{RI}, \tag{5}$$

where $CI$ is the consistency index:

$$CI = \frac{\lambda_{\max} - 1}{n-1}, \tag{6}$$

$\lambda_{\max}$ and $n$ being respectively the maximum (Perron) eigenvalue and the size of the matrix, and $RI$ the random index (Saaty, 1977).

## 2.4 The TOPSIS to rank the Pareto optimal solutions

The TOPSIS is based on the concept of distance to a positive ideal solution and to a negative ideal solution (aka nadir). The best alternative is characterized by the shortest distance to the former and the largest to the later.

TOPSIS's input data are a preliminary collection of a decision-making matrix whose cells contain evaluations of alternatives under the given criteria, and the vector of criteria weights reflecting their mutual importance.

To rank the alternatives through TOPSIS, the following phases are implemented.

1. Statement of the assessment $g_{ij}$ of each alternative $i$ under each criterion $j$.

2. Computation of the weighted and normalized decision matrix where the generic element $u_{ij}$ is:

$$u_{ij} = w_j \cdot z_{ij}, \forall i, \forall j, \tag{7}$$

$w_j$ being the weight of criterion $j$, and $z_{ij}$ the score of the generic solution $i$ under criterion $j$, normalized by:

$$z_{ij} = \frac{g_{ij}}{\sqrt{\sum_{i=1}^{n} g_{ij}^{2}}}, \forall i, \forall j. \tag{8}$$

3. Identification of the positive ideal point $A^*$ and the negative ideal point $A^*$:

$$A^* = (u_1^*, \ldots, u_k^*) = \{(\max_i u_{ij} \mid j \in I'), (\min_i u_{ij} \mid j \in I'')\}, \tag{9}$$

$$A^- = (u_1^-, \ldots, u_k^-) = \{(\min_i u_{ij} \mid j \in I'), (\max_i u_{ij} \mid j \in I'')\}, \tag{10}$$

$I'$ and $I''$ being the sets of criteria to be respectively maximized and minimized.

4. Calculation of the distance from each alternative $i$ to the ideal point $A^*$ and to the nadir point $A^-$:

$$S_i^* = \sqrt{\sum_{j=1}^{k} \left(u_{ij} - u_j^*\right)^2}, i = 1, \ldots n, \tag{11}$$

$$S_i^- = \sqrt{\sum_{j=1}^{k} \left(u_{ij} - u_j^-\right)^2}, i = 1, \ldots n. \tag{12}$$

5. Calculation of the closeness coefficient $C_i^*$ for each solution $i$ to understand how well alternative $i$ performs with respect to the ideal solutions:

$$C_i^* = \frac{s_i^-}{s_i^- + s_i^*} \qquad 0 \le C_i^* \le 1 \qquad \forall i. \tag{13}$$

6. Ranking the alternatives according to the values of the closeness coefficients. Specifically, referring to two generic solutions $i$ and $z$, if $C_i^* \ge C_z^*$ then alternative $i$ must be preferred to alternative $z$.

## 3 Case study

The combined approach for optimal pump scheduling is applied to the D-town network, a benchmark WDN presented in (Stokes *et al.* 2012). This network is formed by 396 nodes, 13 pumps and 4 pressure reducing valves. It has been explored in the literature from the energy and leakage management points of view. The D-town has, by default, 5 DMAs divided by the pump stations. Using these DMAs, three scenarios for pump scheduling have been developed. The first one, so-called base scenario, $S_1$, does not consider leakage in the hydraulic simulations. The second, $S_2$, and the third $S_3$, consider leaks modelled as emitters in EPANET for all demand nodes in DMAs #5 and #2, respectively.

To solve the optimization problem, the NSGA-II algorithm implemented in Matlab is run using 900 random individuals. The objective functions (1) to (4) are evaluated based on hydraulic simulations also run in Matlab, using the EPANET toolkit version. The three scenarios are run using the same NSGA-II parameters for crossover, elitism and population size.

To work on the Pareto front, the stated MCDM approach is conducted. First, the following four criteria $C_1$ to $C_4$ are considered:

- Operational cost: cost of energy spent to operate the pumps in 24h.
- Operational lack of service, herein considered as pressure deficit at the demand nodes.

- Pressure uniformity (PU) parameter, for evaluating pressure compliance. It allows to assess the pressure in the system in terms of the difference between the operational and the minimal and average pressures in the system. Less uniform pressure zones, with higher pressure difference values, correspond to bigger values of PU.
- The resilience of the network, calculated as proposed in (Todini, 2000).

The rationale for selecting these criteria is clear. The higher the energy cost, the lower the pressure deficit in the water network, since more expensive operations are related to longer use of pumps, thus putting more hydraulic head into the system. The inverse correlation cost vs pressure deficit holds for all scenarios. An important point is the pressure deficit observed for the leakage scenarios. Operation under leakage conditions should produce positive pressure (condition for operation); however, this minimal pressure may be not reached, as leakage scenarios impair the water supply process, and the full demand cannot be delivered. Furthermore, the operational cost has an inverse relationship with the switches of the pumps. Larger numbers of switches allow better pump management, saving energy; however, this may impair the future behaviour of the pumps. Lastly, tank deficit increases with the operational costs, since the higher the hydraulic head in the network, the higher the volume overflowed from the tanks.

Figure 1 shows 3-D representations of these criteria for scenario $S_1$. The ideas in the previous rationale and a natural clustering of the solutions, depending on PU and resilience may be observed.

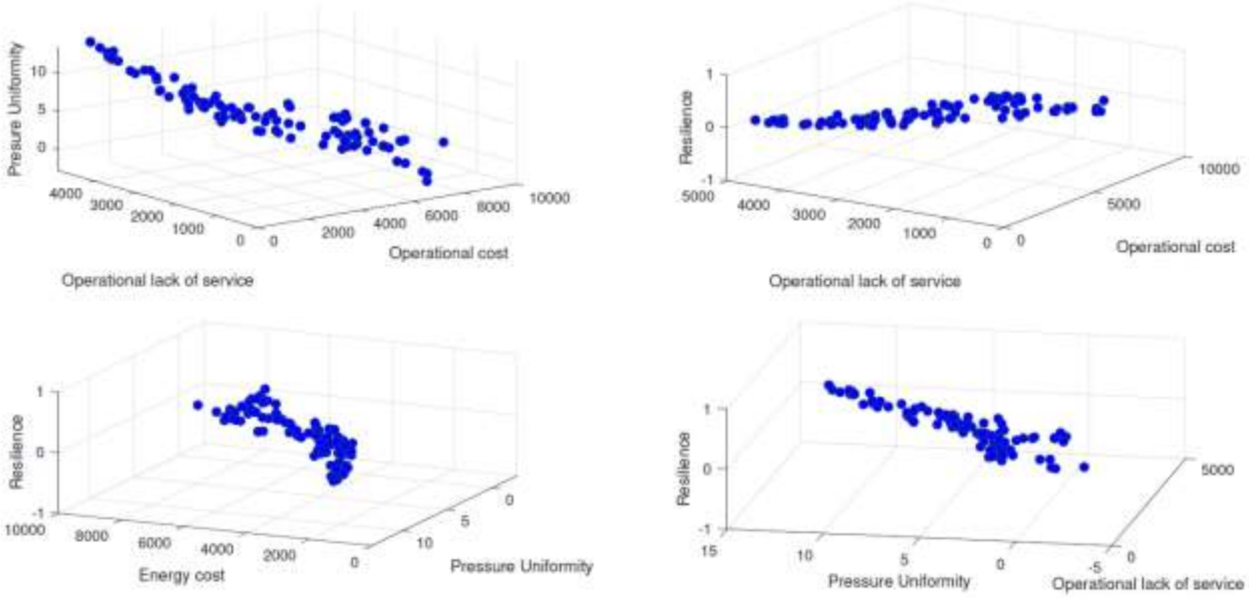


Figure 1. 3-D representations of Pareto front for scenario $S_1$

Now the AHP is applied to weight these criteria. An expert on water systems pairwise compares them using the Saaty scale. The corresponding PCM and the vector of weights are given in Table 1, which also shows an acceptable value of *CR*.

Table 1. Pairwise comparison matrix, criteria weights and *CR* value

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | Weights | *CR* |
|---|---|---|---|---|---|---|
| $C_1$ | 1 | 2 | 1/3 | 1/2 | 12.61% | 0.0539 |
| $C_2$ | 1/2 | 1 | 1/3 | ¼ | 8.94% | |
| $C_3$ | 3 | 3 | 1 | 1/3 | 26.11% | |
| $C_4$ | 4 | 4 | 3 | 1 | 52.34% | |

Finally, TOPSIS is applied to rank the Pareto solutions found for each scenario. The same vector of criteria weights (Table 1) is considered for the three scenarios. The Pareto fronts are respectively made up of 315 solutions for $S_1$, and 158 for $S_2$ and $S_3$. The solutions have been codified with a code $PS_{i,n}$, $i$ varying from 1 to 3 representing the scenario, and $n$ varying from 1 to 315 for $S_1$ and from 1 to 158 for $S_2$ and $S_3$. Also, each alternative has been quantitatively evaluated under the four considered criteria. It is important to note that the first three criteria (cost, lack of service and pressure uniformity) are minimized whereas the fourth criterion (resilience) is maximized. Three pairs of ideal positive and negative points have been calculated, one for each weighted, normalized decision-making matrix, respectively:

- $S_1$: $A^*$ = (0.0031; 3.7253E-05; 0.0114; 0.50389) and $A^-$ = (0.01115; 0.0105; 0.0162; 0);
- $S_2$: $A^*$ = (0.0031; 1.9768E-11; 0.01886; 0) and $A^-$ = (0.0191; 0.0215; 0.0223; 0);
- $S_3$: $A^*$ = (0.0034; 4.7114E-12; 9.0992E-07; 0) and $A^-$ = (0.0219; 0.0159; 0.0696; 0);

Using TOPSIS, the alternatives rankings for the three scenarios are obtained. Their first ten positions, according to the closeness coefficient values, are presented in Tables 2 to 4.

Table 2. Final ranking reporting 10 out of 315 Pareto solutions - scenario $S_1$

| Ranking position | Solution | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_i^*$ |
|---|---|---|---|---|---|---|
| 1 | $PS_{1,272}$ | 1.16E+05 | 4.88E+04 | 4.98E+02 | 3.10E+00 | 0.981894618 |
| 2 | $PS_{1,219}$ | 8.60E+04 | 6.84E+05 | 4.66E+02 | 8.70E-01 | 0.281168081 |
| 3 | $PS_{1,171}$ | 1.04E+05 | 1.56E+05 | 4.80E+02 | 0.00E+00 | 0.020421963 |
| 4 | $PS_{1,17}$ | 9.59E+04 | 5.58E+05 | 4.62E+02 | 0.00E+00 | 0.020170845 |
| 5 | $PS_{1,270}$ | 9.59E+04 | 5.58E+05 | 4.62E+02 | 0.00E+00 | 0.020170845 |
| 6 | $PS_{1,21}$ | 9.70E+04 | 5.36E+05 | 4.62E+02 | 0.00E+00 | 0.020167029 |
| 7 | $PS_{1,20}$ | 1.02E+05 | 4.28E+05 | 4.67E+02 | 0.00E+00 | 0.020134729 |
| 8 | $PS_{1,22}$ | 1.04E+05 | 4.16E+05 | 4.67E+02 | 0.00E+00 | 0.020110377 |
| 9 | $PS_{1,16}$ | 9.76E+04 | 5.22E+05 | 4.72E+02 | 0.00E+00 | 0.020098744 |
| 10 | $PS_{1,298}$ | 5.52E+04 | 6.58E+06 | 4.22E+02 | 0.00E+00 | 0.020098744 |

Table 3. Final ranking reporting 10 out of 158 Pareto solutions - scenario $S_2$

| Ranking position | Solution | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_i^*$ |
|---|---|---|---|---|---|---|
| 1 | $PS_{2,29}$ | 2.19E+03 | 5.94E+09 | 4.42E+01 | 0.00E+00 | 0.794862706 |
| 2 | $PS_{2,140}$ | 2.43E+03 | 4.37E+09 | 4.43E+01 | 0.00E+00 | 0.787411486 |
| 3 | $PS_{2,12}$ | 2.41E+03 | 5.56E+09 | 4.35E+01 | 0.00E+00 | 0.782439817 |
| 4 | $PS_{2,99}$ | 2.07E+03 | 8.17E+09 | 4.40E+01 | 0.00E+00 | 0.781804291 |
| 5 | $PS_{2,95}$ | 2.56E+03 | 3.49E+09 | 4.43E+01 | 0.00E+00 | 0.781687657 |
| 6 | $PS_{2,17}$ | 2.54E+03 | 3.86E+09 | 4.43E+01 | 0.00E+00 | 0.78076911 |
| 7 | $PS_{2,82}$ | 2.59E+03 | 3.49E+09 | 4.43E+01 | 0.00E+00 | 0.778167972 |
| 8 | $PS_{2,103}$ | 2.08E+03 | 8.61E+09 | 4.40E+01 | 0.00E+00 | 0.775155341 |
| 9 | $PS_{2,69}$ | 2.63E+03 | 3.43E+09 | 4.44E+01 | 0.00E+00 | 0.774737863 |
| 10 | $PS_{2,43}$ | 2.14E+03 | 8.17E+09 | 4.42E+01 | 0.00E+00 | 0.774729253 |

Table 4. Final ranking reporting 10 out of 158 Pareto solutions - scenario $S_3$

| Ranking position | Solution | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_i^*$ |
|---|---|---|---|---|---|---|
| 1 | $PS_{3,110}$ | 2.23E+03 | 1.59E+10 | 4.37E+01 | 0.00E+00 | 0.933566367 |
| 2 | $PS_{3,109}$ | 2.08E+03 | 1.91E+10 | 4.28E+01 | 0.00E+00 | 0.932822453 |
| 3 | $PS_{3,13}$ | 2.38E+03 | 1.28E+10 | 4.28E+01 | 0.00E+00 | 0.932651072 |
| 4 | $PS_{3,132}$ | 2.06E+03 | 1.99E+10 | 4.28E+01 | 0.00E+00 | 0.931898161 |
| 5 | $PS_{3,146}$ | 2.34E+03 | 1.50E+10 | 4.28E+01 | 0.00E+00 | 0.931139005 |
| 6 | $PS_{3,36}$ | 2.40E+03 | 1.46E+10 | 4.30E+01 | 0.00E+00 | 0.929619327 |
| 7 | $PS_{3,155}$ | 2.49E+03 | 1.21E+10 | 4.29E+01 | 0.00E+00 | 0.929596304 |
| 8 | $PS_{3,133}$ | 2.01E+03 | 2.21E+10 | 4.26E+01 | 0.00E+00 | 0.928968974 |
| 9 | $PS_{3,105}$ | 2.28E+03 | 1.80E+10 | 4.63E+01 | 0.00E+00 | 0.928771652 |
| 10 | $PS_{3,139}$ | 1.94E+03 | 2.32E+10 | 4.13E+01 | 0.00E+00 | 0.928555576 |

The solutions representing the best trade off among the optimal alternatives, according to the evaluations of the considered criteria, are, respectively, $PS_{1,272}$, $PS_{2,29}$ and $PS_{3,110}$.

To evaluate the effects of leakage in the optimal solution, leaks were added for each pipe. The leakage model (14) considers the pressure-driven model, in which the pressure at the orifice of a pipe $m$ is taken as the mean value between the upstream, $P^{u}_{m,t}$, and the downstream, $P^{d}_{m,t}$, pressures. Coefficients $\beta$ and $\alpha$ depend on the leakage features; in this work, the adopted values are $10^{-6}$ and 0.9, respectively.

$$Q^{leak}_{t,m} = \beta\left(\frac{P^{u}_{m,t} + P^{d}_{m,t}}{2}\right)^{\alpha}. \tag{14}$$

In terms of the four criteria, solutions $PS_{2,29}$ and $PS_{3,110}$, evaluated under leakage conditions present an increase of energy consumption and of PU, while resilience decreases; also, the pumps work out of the optimal operational point, resulting in lower efficiency. As leakage changes the operational point of pumps and the pressure in the network, PU increases, thus pointing to lower pressure uniformity in the system.

## 4 Discussion and future developments

Operation of water networks under high leakage rates is hard from the efficiency point of view. Parameters related to reliability, such as resilience, are indeed strongly affected by leaks. The results of multi-objective optimization for leakage scenarios try to find a trade-off between the pressure deficit and the costs. For some pressure deficits, the method is not able to find low-cost operation. For leakage scenarios, many solutions exhibit a resilience index of 0. It means that the minimal pressure is not respected. This situation does not occur for the base scenario. The criteria values for the base scenario do not present natural clusters, as observed in Figure 1, turning the final choice of a single solution (among those belonging to the Pareto front) an even harder task.

The use of multi-objective optimization allows to treat the real physical and operational problems without penalty functions. Moreover, this approach generates an entire set of optimal solutions. Without any additional information, it is not possible to select a single solution from the Pareto front as the best one. Multi-criteria analysis is useful for water distribution operators to help find the most suitable operation.

In our case, the MCDM combined approach of AHP and TOPSIS has confirmed to be useful to get the ranking of solutions belonging to the Pareto front. Solutions in the first positions of the rankings represent the best trade-off according to the considered criteria. Three rankings have been calculated by applying TOPSIS in three different scenarios and, within the three sets of optimal Pareto solutions, the alternatives $PS_{1,272}$, $PS_{2,29}$ and $PS_{3,110}$ occupy the first positions.

Beside the usefulness of ranking the optimal solutions on the Pareto front, what suggests which solution may preferably be implemented, a possible future development of the present work regards the classification of alternatives into ordered classes. Indeed, classifying alternatives permits to acquire a clearer overview about each of them and to evaluate their global goodness according to various aspects. A helpful method to undertake such clustering is ELECTRE TRI (Roy, 2002), a method of the family ELECTRE initially introduced by Roy (1968). ELECTRE TRI permits to directly visualize the assignment of solutions to classes by means of a two-stage procedure developing first an outranking relation characterizing the comparison between each alternative and the limits of the classes, and then making use of that outranking relation to assign each alternative to a specific class. As asserted by Certa *et al.* (2017) the application of ELECTRE TRI presents various strengths. Among them, the technique requires reasonable computational effort to achieve the final classification, and the class assigned to a specific solution can be easily traced back. We believe that the results obtained in the present paper can be complemented and further developed by means of the use of ELECTRE TRI, which allows to manage large numbers of alternatives, as in the case of the proposed application. Indeed, this method may help decision makers in the water supply field to deal with complex choices by evaluating solutions on the basis of the classes they belong to.

## 5 Conclusions

Management of WDNs requires great attention in the context of urban and climate changes. Optimal schedule of pumps involves many physical and operational constraints, turning single-objective optimization hard, since the use of penalty functions modifies the search space and often creates local minima. In contrast, multi-objective optimization results in a Pareto front of solutions; however, the final selection of a unique solution is a hard task for real-time operation. In this regard, this work presents a multi-objective approach coupled to a multi-criteria analysis for pump scheduling.

Furthermore, an integrated MCDM approach making use of AHP and TOPSIS is proposed to first calculate the weights of the involved criteria (namely cost, operational lack of service, pressure uniformity and network resilience) using water system expertise, and then get the final ranking of solutions on the Pareto front. The TOPSIS procedure is repeated for the various considered scenarios by using the same vector of criteria weights. The addressed case study aims to select the most suitable solution under various conditions according to the evaluation of the four criteria. We can observe that, in all the considered cases, the final solutions present interesting features both in terms of cost and operational indexes. Even if resilience is low, the operations under high leakage rates are not usual, but should be taken into account to guarantee maximal efficiency. Moreover, the evaluation of these solutions under leakage scenarios, points to the modifications of the performance indexes, resulting in cost increase and resilience reduction.

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