Multi-criteria analysis applied to multi-objective optimal pump scheduling in water systems

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ABSTRACT

This work presents a multi-criteria-based approach to automatically select specific non-dominated solutions from a Pareto front previously obtained using multi-objective optimization to find optimal solutions for pump control in a water supply system. Optimal operation of pumps in these utilities is paramount to enable water companies achieving energy efficiency in their systems. The Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS) is used to rank the Pareto solutions found by the Non-Dominated Sorting Genetic Algorithm (NSGA-II) employed to solve the multi-objective problem. Various scenarios are evaluated under leakage uncertainty conditions, resulting in fuzzy solutions for the Pareto front. This paper shows the suitability of the approach to quasi real-world problems. In our case-study, the obtained solutions for scenarios including leakage represent the best trade-off among the optimal solutions, under some considered criteria, namely, operational cost, operational lack of service, pressure uniformity and network resilience. Potential future developments could include the use of clustering alternatives to evaluate the goodness of each solution under the considered evaluation criteria.

Key words | multi-criteria analysis, multi-objective optimization, optimal pump scheduling, water distribution systems

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INTRODUCTION

Operation of water distribution networks (WDNs) encompasses numerous manoeuvres of pumps and valves. Safe and efficient operation may reduce energy consumption in pumping stations, responsible for a significant energy consumption, and control 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 continuity of supply and energy consumption.

The problem of optimal control considers bounds for pressure, tank levels and switches of pumps' statuses, to reduce start-stop cycles of pumps. Moreover, a crucial element in real networks simulation is leakage. Hydraulic simulations considering leakage scenarios can help water utilities devise optimal pump control.

The literature (see Mala-Jetmarova *et al.* (2017) for an exhaustive literature review) presents works using linear programming (Jowitt & Xu 1990), dynamic programming (Jowitt & Germanopoulos 1992), and evolutionary algorithms, such as Genetic Algorithms (Farmani *et al.* 2007). The application of derivative-dependent methods is impractical due to such aspects as non-linearity and discontinuity characterising hydraulic problems. With the increase of computational capacity and the huge availability of data, real-time optimal control has also been exploited, by linking

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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 using meta-heuristic algorithms. Derivative-free methods are useful for 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 make 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 make the search process even harder (Brentan *et al.* 2018).

As an alternative to single-objective algorithms, various bio-inspired, multi-objective algorithms (MOAs) have gained popularity in the field (Montalvo *et al.* 2014; Odan *et al.* 2015). For MOAs, constraints are handled as objectives to reach. However, instead of a single solution, a MOA approach produces a 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, and a large number of solutions makes the decision hard. In this scenario, this paper proposes to manage the solutions obtained from the multi-objective optimization process using a suitable multi-criteria decision-making (MCDM) approach to rank the Pareto front solutions according to several weighted criteria namely, operational cost, operational lack of service, Pressure uniformity (PU) and network resilience.

The literature (Hadas & Nahum 2016; Hamdan & Cheaitou 2017) 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 (Zaidan *et al.* 2015; Zak & Kruszynski 2015) supports the integration of the AHP with other MCDM techniques to make final results more trustworthy.

After weighting the evaluation criteria relevant to the decision-making process under study, this paper uses Fuzzy Technique for Order of Preference by Similarity to Ideal Solution (FTOPSIS), developed by Chen (2000), to get a final ranking of the fuzzy solutions on the Pareto front, thus effectively managing uncertainty.

As a further development of a previous research (Carpitella *et al.* 2018a), this paper proposes a revised approach, increasing the degree of trustworthiness of the final results. First, the fuzzy Pareto front under leakage scenarios is obtained. The D-town network is used to test the impact of leakage on control decisions. A base scenario without leakage is used to find optimal operations using NSGA-II. The options are applied to scenarios with leakage on various district metered areas (DMAs). Each scenario is then evaluated in terms of operational cost, operation lack of service, PU and resilience. Then, the aim is to aid decision-making by ranking the solutions (Kurek & Ostfeld 2013) using FTOPSIS; criteria weights are previously calculated using AHP. This will show those alternatives exhibiting the best trade-off according to various aspects herein considered of primary importance.

MULTI-OBJECTIVE OPTIMIZATION AND MULTI-CRITERIA ANALYSIS

Optimal pump scheduling

Consumption patterns are diverse and vary in several ways. Water demand dynamics, despite the presence of tanks in WDNs, make pump operation a complex decision problem. To tackle this problem, mathematical optimization algorithms are applied to schedule pumping 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 α at time step t, with efficiency $\eta_{i,t}$. Finally, γ is the specific weight of water, Δt 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:

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

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

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

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.

Non-dominated sorting genetic algorithm – NSGA-II

As for other WDN 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 cannot guarantee an optimal real solution. A robust MOA will desirably make 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 and elitism, and allows user-adjusted 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.

The FTOPSIS to rank the Pareto fuzzy solutions

This section provides the reader with a brief description of the FTOPSIS method.

The first step consists in collecting data within the so-called fuzzy decision matrix $\tilde{X}$:

$$\tilde{X} = \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{bmatrix} \tag{5}$$

where $\tilde{x}_{ij}$ is the fuzzy number that represents the rating of alternative i under criterion j. Triangular fuzzy numbers (TFNs), characterized by ordered triples are used here:

$$\tilde{x}_{ij} = (a_{ij},\ b_{ij},\ c_{ij}) \tag{6}$$

After the preliminary collection of fuzzy input data, $\tilde{X}$ must be weighted and normalized with relation to each criterion to obtain the normalized decision matrix $\tilde{U}$:

$$\tilde{U} = \begin{bmatrix} \tilde{u}_{11} & \cdots & \tilde{u}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{u}_{m1} & \cdots & \tilde{u}_{mn} \end{bmatrix} \tag{7}$$

where

$$\tilde{u}_{ij} = \left(\frac{a_{ij}}{c_j^*},\ \frac{b_{ij}}{c_j^*},\ \frac{c_{ij}}{c_j^*} \right) \cdot w_j, \quad j \in I' \tag{8}$$

$$\tilde{u}_{ij} = \left(\frac{a_j^-}{c_{ij}},\ \frac{a_j^-}{b_{ij}},\ \frac{a_j^-}{a_{ij}} \right) \cdot w_j, \quad j \in I'' \tag{9}$$

I' being the subset of criteria to be maximized, I'' the subset of criteria to be minimized, w_j the relative importance weight of criterion j, and c_j^* and a_j^- calculated as:

$$c_j^* = \max_i c_{ij} \text{ if } j \in I' \tag{10}$$

$$a_j^- = \min_i a_{ij} \text{ if } j \in I'' \tag{11}$$

Referring to matrix $\tilde{U}$, each fuzzy alternative has to be compared with both a fuzzy positive ideal solution A^* and a fuzzy negative ideal solution A^-, namely:

$$A^* = (\tilde{u}_1^*,\ \tilde{u}_2^*,\ \ldots,\ \tilde{u}_n^*) \tag{12}$$

$$A^- = (\tilde{u}_1^-,\ \tilde{u}_2^-,\ \ldots,\ \tilde{u}_n^-) \tag{13}$$

where $\tilde{u}_j^* = (1,\ 1,\ 1)$ and $\tilde{u}_j^- = (0,\ 0,\ 0)$, $j = 1 \ldots n$. The comparison between each alternative and these points is expressed in terms of their distance, computed through the vertex method (Chen 2000). According to this method, the distance $d(\tilde{m},\ \tilde{n})$ between $\tilde{m} = (m_1,\ m_2,\ m_3)$ and $\tilde{n} = (n_1,\ n_2,\ n_3)$ is the crisp value:

$$d(\tilde{m},\ \tilde{n}) = \sqrt{\frac{1}{3}[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2]} \tag{14}$$

For each alternative i, aggregating with respect to the whole set of criteria, the related distances from A^* and A^- are then calculated as:

$$d_i^* = \sum_{j=1}^{n} d(\tilde{u}_{ij}, \tilde{u}_j^*) i = 1 \ldots n \tag{15}$$

$$d_i^- = \sum_{j=1}^{n} d(\tilde{u}_{ij}, \tilde{u}_j^-) i = 1 \ldots n \tag{16}$$

The last step consists in calculating, for each alternative, the closeness coefficient CC_i to get the final ranking:

$$CC_i = \frac{d_i^-}{d_i^- + d_i^*} \tag{17}$$

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 viewpoints. The D-town has, by default, 5 DMAs determined by the pumping stations. Using these DMAs, three scenarios for pump scheduling have been developed. The first one, a 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. Modelling leakage in WDNs is difficult, since the pressure dependence of leaks makes the model computationally more complex and the physical parameters of the orifice are uncertainties to be calibrated in the model. In this sense, scenarios S_2 and S_3 are simulated with various parameters for the emitters, resulting in a fuzzy solution for the problem.

To evaluate the effects of leakage, leaks were added for each pipe. The leakage model (18) is a pressure-driven-based model, in which the pressure at the orifice of a pipe m is taken as the average between the upstream, $P_{m,t}^u$, and the downstream, $P_{m,t}^d$, pressures. Coefficients β and α depend on the leakage features; in this work, the adopted values are 10^{-6} and 0.9, respectively.

$$Q_{m,t}^{leak} = \beta\left(\frac{P_{m,t}^u + P_{m,t}^d}{2}\right)^\alpha \tag{18}$$

To solve the optimization problem, the NSGA-II algorithm implemented in Matlab is run using 900 random individuals, cross-over fraction 0.8, and elitism rate 0.05. 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 used. First, the following four criteria C_1 to C_4 are considered:

- C_1: Operational cost: cost of energy spent to operate the pumps for 24 h.
- C_2: Operational lack of service, herein considered as pressure deficit at the demand nodes.

- C_3: 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.
- C_4: 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 not be reached, as leakage scenarios impair water supply, 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 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.

With the base solution for each scenario, the operations for S_2 and S_3 are subjected to two leakage values. These values generate fuzzy Pareto fronts. The Pareto fronts are handled by TOPSIS to select an optimal operation based on various leakage scenarios.

The vector of criteria weights has been produced by a preliminary application of the AHP technique, through the support of an expert in the field. The degrees of importance for the mentioned criteria are: C_1: 12.61%, C_2: 8.94%, C_3: 26.11/, C_4: 52.34%. This confirms the great prominence of aspects related to network resilience. For the sake of conciseness, the AHP process is omitted here.

Using these weights, FTOPSIS is applied to rank the fuzzy Pareto solutions found for each scenario. The Pareto fronts are respectively made up of 315 solutions for S_1, and 105 for both 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 105 for S_2 and S_3. To apply the FTOPSIS, let us note that the first

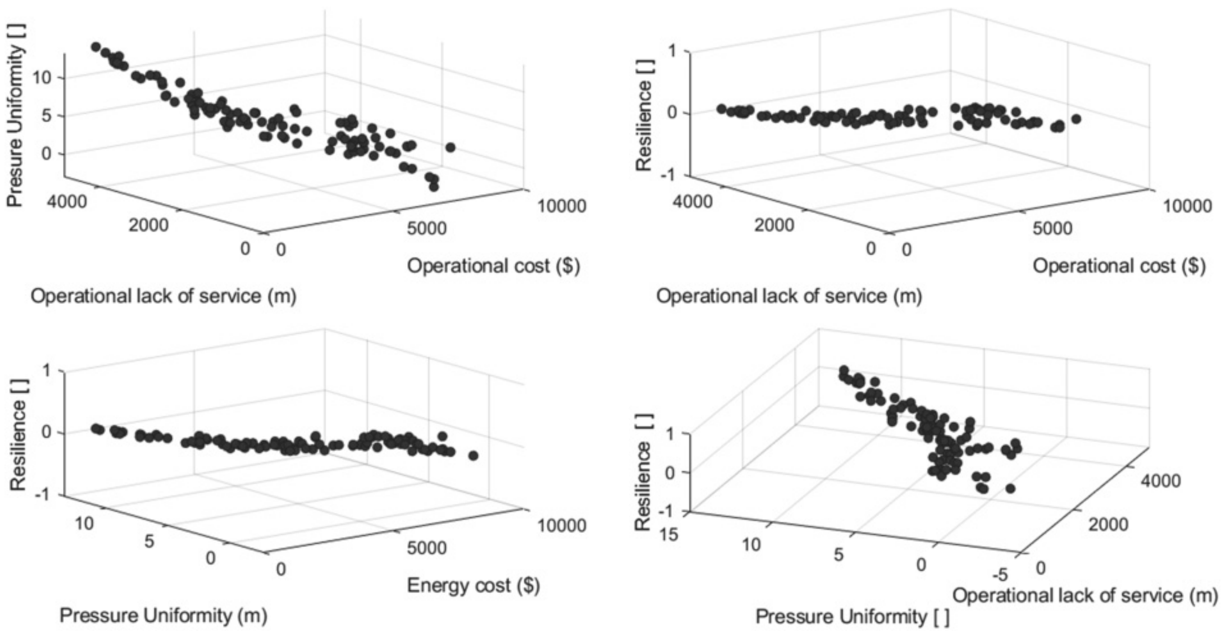

Figure 1 | 3-D representations of the Pareto solutions for scenario S_1.

Table 1 | Final ranking reporting 5 out of 315 Pareto fuzzy solutions - scenario S_1

Ranking	ID	C_1	C_2	C_3	C_4	CC_i
1	$PS_{1,272}$	1.16E + 05	4.88E + 04	4.98E + 0	3.10E + 00	0.208341676
2	$PS_{1,219}$	8.60E + 04	6.84E + 05	4.66E + 02	8.70E − 01	0.099690155
3	$PS_{1,52}$	4.13E + 04	1.19E + 07	3.61E + 0	0.00E + 00	0.088569587
4	$PS_{1,111}$	3.22E + 04	1.31E + 07	4.11E + 02	0.00E + 00	0.087774002
5	$PS_{1,220}$	4.34E + 04	1.00E + 07	3.74E + 02	0.00E + 00	0.08529466

three criteria (cost, lack of service and PU) are minimized whereas the fourth criterion (resilience) is maximized. This means that, when it comes to the use of formulas (8) and (9), criterion C_4 belongs to the subset I', whereas criteria C_1, C_2 and C_3 belong to the subset I''.

The first five positions in the final rankings of alternatives for the three scenarios, according to the closeness coefficient values, are presented in Tables 1–3. Let us observe that for S_1, being a scenario without leakage, just crisp values were obtained and, herein represented by singletons.

The solutions representing the best trade-off among the optimal alternatives, according to the evaluations of the considered criteria, are, respectively, $PS_{1,272}$, $PS_{2,42}$ and $PS_{3,92}$.

Regarding the four criteria, solutions $PS_{2,42}$ and $PS_{3,92}$ evaluated under leakage conditions increase the energy consumption for both scenarios. As expected, the energy efficiency of the water network is impaired by the leakage presence. Optimal operations are obtained in scenarios without leakage, while loss of efficiency is clear under leakage scenarios. Also, the PU is harmed by leakage, increasing the PU index. Strongly linked to the PU, the operational lack of service is also harmed by leakage, since the flow rate should increase to deliver the nodal demand and also the leaks, thus increasing the head loss.

Scenario S_3 reveals an important feature and a clear advantage of the multi-criteria analysis. The first and second selected solutions, $PS_{3,92}$ and $PS_{3,12}$, are the only resilient solutions, that is to say, with C_4 greater than 0. This means that the optimal operation for this scenario can be applied under leakage conditions without impairing the service, despite the efficiency is lower than expected.

DISCUSSION AND FUTURE DEVELOPMENTS

Operation of water networks under high leakage rates is hard from the efficiency viewpoint. Reliability-related parameters, such as resilience, are strongly affected by leakage. The results of multi-objective optimization for leakage scenarios find a trade-off between pressure deficit and cost. For some pressure deficits, the method is unable to find low-cost operation. For leakage scenarios, many solutions exhibit a resilience index of zero. It means that

Table 2 | Final ranking reporting 5 out of 105 Pareto fuzzy solutions - scenario S_2

Ranking	ID	C_1	C_2	C_3	C_4	CC_i
1	$PS_{2,42}$	(5.92E + 03, 5.93E + 03, 5.93E + 03)	(4.98E + 02, 4.98E + 02, 6.87E + 02)	(9.73E − 01, 9.73E − 01, 2.08E + 00)	(0.00E + 00, 0.00E + 00, 0.00E + 00)	0.198613652
2	$PS_{2,63}$	(7.46E + 03, 7.46E + 03, 7.46E + 03)	(1.00E + 00, 1.00E + 00, 5.00E + 00)	(1.87E + 00, 1.88E + 00, 1.88E + 00)	(0.00E + 00, 0.00E + 00, 0.00E + 00)	0.192422739
3	$PS_{2,51}$	(6.10E + 03, 6.11E + 03, 6.11E + 03)	(4.10E + 01, 4.10E + 01, 1.05E + 02)	(1.83E + 00, 1.83E + 00, 1.83E + 00)	(0.00E + 00, 0.00E + 00, 0.00E + 00)	0.177835939
4	$PS_{2,7}$	(6.17E + 03, 6.17E + 03, 6.17E + 03)	(3.20E + 01, 3.20E + 01, 6.10E + 01)	(1.84E + 00, 1.84E + 00, 1.84E + 00)	(0.00E + 00, 0.00E + 00, 0.00E + 00)	0.177708953
5	$PS_{2,104}$	(6.42E + 03, 6.42E + 03, 6.42E + 03)	(4.70E + 01, 4.70E + 01, 1.01E + 02)	(1.86E + 00, 1.87E + 00, 1.87E + 00)	(0.00E + 00, 0.00E + 00, 0.00E + 00)	0.176532111

Table 3 | Final ranking reporting 5 out of 105 Pareto fuzzy solutions - scenario S_3

Ranking	ID	C_1	C_2	C_3	C_4	CC_i
1	$PS_{3,92}$	(9.27E + 03, 9.27E + 03, 9.29E + 03)	(1.00E + 00, 1.00E + 00, 1.00E + 00)	(1.92E + 00, 1.97E + 00, 1.97E + 00)	(3.81E – 01, 3.89E – 01, 3.99E – 01)	0.217996865
2	$PS_{3,12}$	(1.09E + 04, 1.09E + 04, 1.09E + 04)	(1.00E + 00, 1.00E + 00, 1.00E + 00)	(2.02E + 00, 2.07E + 00, 2.07E + 00)	(3.93E – 01, 3.99E – 01, 4,05E – 01)	0.216849352
3	$PS_{3,47}$	(1.09E + 04, 1.09E + 04, 1.09E + 04)	(1.00E + 00, 1.00E + 00, 1.00E + 00)	(2.01E + 00, 2.05E + 00, 2.05E + 00)	(0.00E + 00, 0.00E + 00, 0.00E + 00)	0.088201671
4	$PS_{3,53}$	(6.35E + 03, 6.47E + 03, 6.47E + 03)	(2.90E + 01, 2.90E + 01, 1.53E + 02)	(1.83E + 00, 1.86E + 00, 1.86E + 00)	(0.00E + 00, 0.00E + 00, 0.00E + 00)	0.077382969
5	$PS_{3,55}$	(6.33E + 03, 6.46E + 03, 6.46E + 03)	(8.30E + 01, 8.30E + 01, 4.85E + 02)	(1.85E + 00, 1.85E + 00, 1.90E + 00)	(0.00E + 00, 0.00E + 00, 0.00E + 00)	0.076505914

the minimum pressure is not accomplished. This situation does not occur for the base scenario. The criteria values for the base scenario do not induce natural clusters, as observed in Figure 1, making the final choice of a single solution (among those belonging to the Pareto front) an even harder task.

Multi-objective optimization generates an entire set of optimal solutions. Without additional information, such a thing as the best solution in undefined. Multi-criteria analysis is useful for water distribution operators to help find the most suitable operation. Uncertainty associated to leakage scenarios can be considered in a number of ways on the fuzzy Pareto front generation. For future works, studies of probability of each leakage scenario can be conducted, in order to find more realistic fuzzy Pareto fronts.

In our case, the combined MCDM-approach of AHP and FTOPSIS has confirmed to be useful to rank the solutions belonging to the Pareto front. Solutions in the first rank positions represent optimal trade-offs for the considered criteria. Three rankings have been calculated by applying FTOPSIS to three scenarios. Alternatives $PS_{1,272}$, $PS_{2,42}$ and $PS_{3,92}$ occupy the first positions, respectively.

Beside the usefulness of these rankings, a potential development of the present work regards the classification of alternatives into ordered classes. Classifying alternatives permits to acquire a clearer view about 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 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. The authors claim that the results obtained in this 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. This method may help decision makers in the water supply field to deal with complex choices by evaluating solutions based on the classes they belong to.

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, making single-objective optimization problematic. 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. This work proposes multi-criteria analysis to help select Pareto front solutions obtained through a multi-objective approach for pump scheduling.

A MCDM approach, FTOPSIS, is proposed to get the final ranking of fuzzy solutions on the Pareto front, under the evaluation of four criteria, namely cost, operational lack of service, PU and network resilience. This approach permits to automatically select an option within a set of optimal solutions by considering leaks and effectively managing uncertainty. The procedure is applied to the considered scenarios by using the same criteria weights, derived from a previous AHP application. The addressed case study shows a practical selection of the most suitable solution according to four evaluation criteria. In all the considered cases, the final solutions present interesting features both in terms of cost and operational indicators. Even for low resilience, operation under high leakage rates should be taken into account to guarantee maximal efficiency. The evaluation of these solutions under leakage scenarios, points to modifications of the performance indexes, resulting in cost increase and resilience reduction.

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