



Multi-objective and multi-criteria analysis for optimal pump scheduling in water systems

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Abstract

This contribution focuses on the problem of optimal pump scheduling, a fundamental element in pursuing operation optimization of water distribution systems. A combined approach of multi-objective optimization and multi-criteria analysis is herein suggested to first find the Pareto front of non-dominated solutions and then to rank them based on a set of weighted criteria. The Non-Dominated Sorting Genetic Algorithm (NSGA-II) is proposed to solve the multi-objective problem, while the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) is used to achieve the final ranking.

1 Introduction

Water distribution network (WDN) operation is responsible for significant energy consumption. Optimal management can be crucial to improve the hydro-energetic efficiency of WDNs, through pump operation at lower prices and leakage reduction by suitable pressure control. Taking into account the complexity of these systems and the highly non-linear nature of the hydraulic equations describing them, hydraulic models coupled with optimization algorithms have been widely applied to design optimal operation strategies.

Several works in the literature have proposed solutions for the optimal pump scheduling problem. Among the used techniques, Linear Programming [1], Dynamic Programming [2] and evolutionary algorithms, such as Genetic Algorithms [3, 4] and Particle Swarm Optimization [5] can be highlighted.

Despite single-objective optimization is able to find interesting solutions, problem-solving using it may be complex, mainly for the application of bio-inspired algorithms, and requires special attention to the constraints. Constraints can be managed through penalty functions, which increase the value of the objective function when constraints are violated. However, penalty functions are hard to be selected and can affect directly the performance of the optimization process. In contrast, multi-objective optimization introduces a new perspective and

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the constraints of the problem may be treated as objectives to meet. Multi-objective algorithms (MOAs) have been widely applied in urban hydraulics. Instead of a single solution, the final response of an MOA is a set of solutions, the so-called Pareto front, which water utility staff can use as an aid in decision-making.

Considering the problem of optimal scheduling of pumps and valves in WDNs, leak reduction by pressure management and minimal pressure of the system are conflicting objectives. This is also the case for energy saving, which requires lower pump operation. Finally, tank level oscillations are also considered. Despite an MOA can be useful to propose various optimal operation solutions, the final decision picked out from the Pareto front may be hard for the operators.

With this perspective, we propose to manage the solutions obtained from the multi-objective optimization process with a suitable multi-criteria decision-making (MCDM) method able to rank the Pareto front solutions.

The literature [6, 7] strongly supports the use of MCDM methods to achieve high effectiveness in decision-making, and several techniques can be applied to ranking purposes [8, 9]. Among others, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), originally proposed by Hwang and Yoon [10] and then further developed in [11], is able to rank a wide number of alternatives on the basis of various evaluation criteria.

A combined approach of these two perspectives is aimed at first finding the Pareto optimal set of solutions and then ranking or classifying them [12] to aid decision-making. This approach can be considered as a driver in implementing the alternative that represents the best trade-off according to the various considered criteria. The process will be supported by analysing feedbacks coming from a team of experts.

2 Optimal pump scheduling

Algorithms for optimum pump scheduling typically combine pumps' statuses within an operational horizon for reducing energy costs. This means to find the best combination of pumps' statuses guaranteeing safe operation of the WDN, while expending a minimum amount of energy. The optimization problem may be stated in terms of energy cost, F_1 , for the pump system as:

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

where N_p is the number of pumps in the system working during time horizon P_e ; $Q(\alpha_{i,t})$ is the pumped flow and $H(\alpha_{i,t})$ is the 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 the water, Δt the time step, one hour in this work, and c_t is the energy cost at time step t .

As an operational problem, the solution of the pump scheduling is constrained by the minimum pressure P_{min} in the system; the oscillation of tank levels between their maximum, $T_{k,max}$, and minimum, $T_{k,min}$; and the number of status switches during the operational horizon. To avoid penalty functions for treating these constraints, a set of objectives, F_2, F_3, F_4 , respectively, can be written for the multi-objective optimization process. For the three mentioned constraints the objective functions are:

$$F_2 = \sum_{j=1}^{N_n} \sum_{t=1}^{P_e} |P_{j,t} - P_{min}|; \quad (2)$$

$$F_3 = \sum_{k=1}^{Nt} \sum_{t=1}^{Pe} |T_{k,t} - T_{k,min}| + \sum_{i=1}^{NT} \sum_{t=1}^{Pe} |T_{k,t} - T_{k,max}|; \quad (3)$$

$$F_4 = \sum_{i=1}^{Np} \sum_{t=1}^{Pe} s_{i,t}; \quad (4)$$

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

3 Multi-objective optimization and multi-criteria analysis

3.1 Non-dominated sorting genetic algorithms - NSGA-II

The NSGA-II is a Genetic Algorithm development for multi-objective problems, proposed in [13]. 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 promote a diverse front of non-dominated solutions.

3.2 The TOPSIS to rank 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.

As input data, TOPSIS uses a decision matrix containing assessment of alternatives under given evaluation criteria, and the vector of criteria weights reflecting the perceptions of the experts involved in the analysis.

To rank the set of alternatives, TOPSIS implements the following phases.

1. Statement of the evaluation 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:

$$u_{ij} = w_j \cdot z_{ij}, \forall i, \forall j. \quad (5)$$

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

$$z_{ij} = \frac{g_{ij}}{\sqrt{\sum_{i=1}^n g_{ij}^2}}, \forall i, \forall j. \quad (6)$$

3. Identification of the ideal point A^* and of the nadir point A^- :

$$A^* = (u_1^*, \dots, u_k^*) = \left\{ (\max_j u_{ij} | j \in I'), (\min_j u_{ij} | j \in I'') \right\}, \quad (7)$$

$$A^- = (u_1^-, \dots, u_k^-) = \left\{ (\min_j u_{ij} | j \in I'), (\max_j u_{ij} | j \in I'') \right\}, \quad (8)$$

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

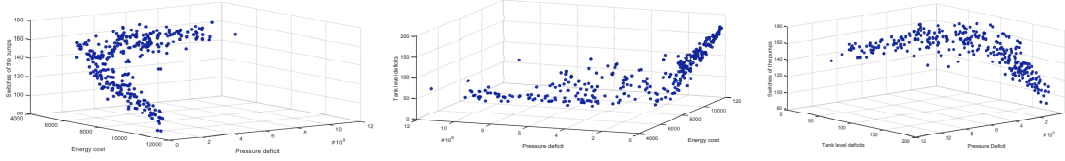


Figure 1: 3-D representation of the Pareto front for the optimal pump scheduling.

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

$$S_i^* = \sqrt{\sum_{j=1}^k (u_{ij} - u_j^*)^2}, i = 1 \dots n. \quad (9)$$

$$S_i^- = \sqrt{\sum_{j=1}^k (u_{ij} - u_j^-)^2}, i = 1 \dots n. \quad (10)$$

5. Calculation of the closeness coefficient C_i^* for each solution i to represent how well i performs with respect to the positive ideal solution:

$$C_i^* = \frac{S_i^-}{S_i^- + S_i^*}, 0 \leq C_i^* \leq 1, \forall i. \quad (11)$$

6. Ranking the alternatives on the basis of the calculated closeness coefficients. Specifically, referring to two generic solutions i and z , if $C_i^* \geq C_z^*$ then solution i must be preferred to solution z .

4 Case study

The combined approach for optimal pump scheduling is applied to the D-town network, a benchmark WDN presented in [14]. 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 NSGA-II algorithm implemented in Matlab was run using 900 random solutions to find the Pareto front for the optimal pump scheduling problem. Figure 1 presents a 3-D representation of the Pareto front considering the schedule of the pumps. It can be highlighted that the more expensive the operation, the lower the deficit of pressure. This correlation is clear, since more expensive operations are related to longer use of pumps, thus putting more hydraulic head into the system. The optimal operational cost increases when the number of switches decreases. Larger number of switches allows better pump management, saving more energy, even if this can 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.

Working on the solutions of the Pareto front, the multi-criteria analysis is conducted to identify what is the more adequate. To such an aim, the following four criteria related to WDN management are considered:

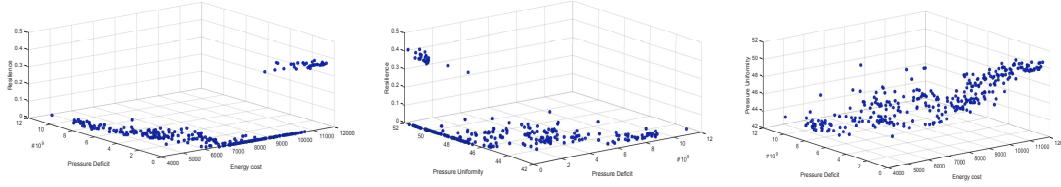


Figure 2: Representation of the criteria for each solution of the Pareto front.

- Operational cost obtained from the Pareto front.
- Operational lack of service, herein considered as pressure deficit at the demand nodes.
- Pressure uniformity (PU) parameter, for evaluating pressure compliance. This parameter 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 high pressure difference values, are found in the network corresponding to bigger values of PU .
- The resilience of the network, calculated as proposed in [15].

To identify the correlations of each criteria with respect to the solutions in the Pareto front, Figure 2 presents a 3-D representation of the criteria parameters.

The TOPSIS methodology was carried out to rank a set of 315 Pareto solutions. Each solution was codified with a code, PS_n , n varying from 1 to 315, and was quantitatively evaluated under the four given criteria, respectively identified as C_1 , C_2 , C_3 and C_4 . The first three criteria have to be minimized whereas the fourth has to be maximized. The ideal and the nadir points for the weighted, normalized decision matrix are, respectively: $A^* = (8.60E-03; 0.00E+00; 1.26E-02, 4.51E-02)$ and $A^- = (2.11E-02; 4.23E-02, 1.53E-02, 0.00E+00)$.

Three scenarios were then analysed: the first considers equal assignment of weights; in the second scenario a lower importance is given to the economic aspect, whereas the third scenario contemplates the prominence of the cost with respect to the other features.

After implementing TOPSIS and achieving the complete ranking of the 315 alternatives, we provide the set of the ten best solutions, the ones in the first ten positions in the ranking according to the closeness coefficient. Results for the three scenarios and the numerical evaluations of the criteria are given in Tables 1 to 3.

By observing the reported results, it is possible to note some variations in the final rankings. The solution PS_{49} appears to be the more suitable trade-off among the optimal alternatives, according to the evaluations of the considered criteria, occupying the first position in two considered scenarios, and the second position in the last scenario.

To evaluate the effects of leakage in the optimal solution, leaks were added for each pipe. The leakage model (see next equation) considers the pressure-driven model, in which the pressure in the leakage orifice of a pipe m is taken as the mean value 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.

$$Q_{t,m}^{leak} = \beta \cdot \left(\frac{P_{m,t}^u + P_{m,t}^d}{2} \right)^\alpha. \quad (12)$$

Table 1: Final ranking for the vector of criteria weights [0.25, 0.25, 0.25, 0.25]

Ranking position	Solution	C_1	C_2	C_3	C_4	C_i^*
1	PS_{49}	9.32E+03	0.00E+00	5.08E+01	4.36E-01	0.876997066
2	PS_{203}	9.39E+03	0.00E+00	5.04E+01	4.31E-01	0.87518652
3	PS_{218}	8.79E+03	1.83E-01	4.86E+01	3.95E-01	0.87194253
4	PS_{47}	9.25E+03	9.79E-01	4.71E+01	3.95E-01	0.863532413
5	PS_{50}	1.00E+04	0.00E+00	5.03E+01	4.13E-01	0.855952728
6	PS_{196}	1.01E+04	0.00E+00	5.03E+01	4.10E-01	0.852093356
7	PS_{234}	9.66E+03	0.00E+00	5.02E+01	3.93E-01	0.851803008
8	PS_{302}	1.03E+04	0.00E+00	5.17E+01	4.13E-01	0.848682341
9	PS_{175}	1.01E+04	0.00E+00	5.02E+01	3.93E-01	0.842288929
10	PS_1	1.05E+04	0.00E+00	5.08E+01	4.08E-01	0.84207829

Table 2: Final ranking for the vector of criteria weights [0.10, 0.30, 0.30, 0.30]

Ranking position	Solution	C_1	C_2	C_3	C_4	C_i^*
1	PS_{49}	9.32E+03	0.00E+00	5.08E+01	4.36E-01	0.943693148
2	PS_{203}	9.39E+03	0.00E+00	5.04E+01	4.31E-01	0.943618474
3	PS_{50}	1.00E+04	0.00E+00	5.03E+01	4.13E-01	0.929216493
4	PS_{196}	1.01E+04	0.00E+00	5.03E+01	4.10E-01	0.925949449
5	PS_{302}	1.03E+04	0.00E+00	5.17E+01	4.13E-01	0.924835185
6	PS_1	1.05E+04	0.00E+00	5.08E+01	4.08E-01	0.920890314
7	PS_{169}	1.06E+04	0.00E+00	5.07E+01	4.07E-01	0.91954257
8	PS_{218}	8.79E+03	1.83E-01	4.86E+01	3.95E-01	0.919142038
9	PS_{47}	9.25E+03	9.79E-01	4.71E+01	3.95E-01	0.919006964
10	PS_{289}	1.11E+04	0.00E+00	5.11E+01	4.10E-01	0.91892125

Table 3: Final ranking for the vector of criteria weights [0.40, 0.20, 0.20, 0.20]

Ranking position	Solution	C_1	C_2	C_3	C_4	C_i^*
1	PS_{218}	8.79E+03	1.83E-01	4.86E+01	3.95E-01	0.794510671
2	PS_{49}	9.32E+03	0.00E+00	5.08E+01	4.36E-01	0.787181766
3	PS_{203}	9.39E+03	0.00E+00	5.04E+01	4.31E-01	0.783915221
4	PS_{47}	9.25E+03	9.79E-01	4.71E+01	3.95E-01	0.777539553
5	PS_{234}	9.66E+03	0.00E+00	5.02E+01	3.93E-01	0.760784162
6	PS_{50}	1.00E+04	0.00E+00	5.03E+01	4.13E-01	0.756493058
7	PS_{196}	1.01E+04	0.00E+00	5.03E+01	4.10E-01	0.751291207
8	PS_{302}	1.03E+04	0.00E+00	5.17E+01	4.13E-01	0.745726008
9	PS_{175}	1.01E+04	0.00E+00	5.02E+01	3.93E-01	0.743955655
10	PS_1	1.05E+04	0.00E+00	5.08E+01	4.08E-01	0.736068121

In terms of the four criteria, the solution PS_{49} evaluated under the leakage condition presents an increase of energy consumption and of PU , while the resilience decreases. In the leakage scenario, 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.

5 Conclusions

The management of WDNs requires great attention in the context of urban and climate changes. The 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, but 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 multicriteria analysis for pump scheduling. The ranking of 315 Pareto solutions has been carried out in the addressed case study, with the aim to select the most suitable solution according to the evaluation of four criteria, namely cost, operational lack of service, pressure uniformity and network resilience. Three scenarios, considering different weights attributed to the mentioned criteria, have been taken into account. The final selected solution presents interesting features in terms of cost and operational indexes, such as PU and resilience. The evaluation of this solution under a leakage scenario, points to the modifications of the performance indexes, resulting in cost increase and resilience reduction.

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