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Research article

# Many-objective optimization model for the flexible design of water distribution networks

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ABSTRACT

This paper proposes a many-objective optimization model for the flexible design of water distribution networks (WDNs), including four objectives. Two objectives are related to the WDNs' hydraulic capacity, the minimization of the pressure deficit and the undelivered demand. The third objective is the traditional cost minimization while the fourth minimizes carbon emissions. These objectives concern network reliability, and financial and environmental concerns. They can give rise to solutions embedding new trade-off in design perspectives. There is a gap in the literature when it comes to dealing with many-objective problems for designing and constructing a WDN over a long-term planning horizon and using a staged design scheme that includes the consideration of uncertainty. A solution obtained through this process can be implemented in the first stage and the WDN is prepared for the possible occurrence of various future scenarios. These scenarios can consider expansions of WDNs to different development areas, in different time stages. Furthermore, defining a multi-staged design allows implementing the design of the first stage and reassessing the whole process in the end of each stage when more plausible future scenarios can be investigated. The solution of complex problems such as these needs improved algorithms to produce the Pareto front and so enable the trade-off between the objectives to be examined. An enhanced algorithm, based on the simulated annealing concept and capable of handling the critical scalability issues encountered in previous algorithms with respect to drawing the Pareto front for many-objective problems where a high-dimensional space is involves, is presented. The results obtained allow a thorough analysis of trade-offs between objectives and confirm the importance of considering the minimization of all those four objectives and the advantages of using a flexible approach to design WDNs to better inform decision makers.

## 1. Introduction

Water distribution network (WDN) design is one of the most complex problems in the management of urban water systems (Mala-Jetmarova et al., 2018). The complexity of the design problem stems mainly from its discrete and nonlinear nature, multiple criteria for evaluation, as well as uncertainties inherent in long-term planning. This work presents a many-objective model for the flexible design of WDNs, based on a multi-stage scheme. The aim is to account for multiple benefits of the design by minimizing four objectives, namely, pressure deficits, undelivered demand, construction costs, and carbon emissions. Many studies of the optimal design of WDNs have been published over the last three decades. Mala-Jetmarova et al. (2018), present a detailed literature review where all the concepts, main contributions, developments, trends and limitations on this subject are analysed and highlighted.

Different approaches have been followed, ranging from the initial attempts in which single objective models were solved by the linear programming gradient method (Alperovits and Shamir, 1977), through nonlinear programming methods (Lansey and Mays, 1989), to the more recent heuristics methods used to solve more complex problems such as real WDNs. Examples of heuristics that dealt with the single objective (cost minimization) problem optimization of WDNs include genetic algorithms (Savic and Walters, 1997), simulated annealing (Cunha and Sousa, 1999), ant colony optimization (Maier et al., 2003) and harmony search (Geem, 2006). The simplest approach to minimizing the cost via a single-objective optimization model was most likely developed because of the high complexity of these systems, and because financial resources to construct infrastructure are always limited. However, approaches involving more objectives have subsequently been devised because WDN design often exhibits multiple, conflicting objectives (Savic, 2002).

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In addition to cost minimization, a considerable body of literature has considered other objectives, mostly using two-objective models. For example, the pressure deficit reduction at nodes as a measure of network reliability was included by Keedwell and Khu (2004), Kapelan et al. (2005) and Fu and Kapelan (2011) for the optimal rehabilitation of an existing WDN (New York Tunnels case study). Similarly, Atiquzzaman et al. (2006) applied the same objective for the Hanoi and Alperovits and Shamir (1977) networks. The minimization of the undelivered demand was used by Tanyimboh and Seyoum (2016) for a real UK case study. The maximization of a network resilience index was included by Wang et al. (2015), while the minimization of greenhouse gas emissions was studied by Wu et al. (2008), Herstein et al. (2009), Wu et al. (2010) and Stokes et al. (2015) for the optimal design and operation of new WDNs. Shokoohi et al. (2017) added the maximization of water quality as another objective. Although the two-objective WDN design problem is sufficiently complex to warrant the use of sophisticated heuristic methods, going beyond two objectives brings additional challenges for optimization methods (Deb, 1999).

Wu et al. (2013) proposed a three-objective model, including minimizing costs, improving reliability and reducing greenhouse gas emissions. Khu and Keedwell (2005) analyse the additional design choices given by an optimization model with six objectives compared with design solutions obtained with a two-objective NSGA-II model. Giustolisi and Berardi (2009) considered four objectives (investment costs, cost of pipe breaks, preferential selection of only one pipe material and reliability) for the rehabilitation of water distribution networks (case study, real UK water distribution network), using the multiobjective genetic algorithm, OPTIMOGA. Fu et al. (2013) solved the rehabilitation and operation of water distribution networks (case study: Anytown) with the following objectives: investment costs, operating costs, hydraulic failure, leakage, water age, and fire-fighting capacity, using the ε-NSGA-II algorithm. However, none of these studies deals with the much more complex problem of the design and construction of a WDN over a long-term planning horizon through a staged design scheme including consideration of uncertainty.

Staged design is important for considering uncertainty issues (e.g., uncertain nodal demands or network deterioration), as it allows intervention at different stages of the planning horizon by defining flexible solutions in the process of WDN development and permitting planners to act (and change decisions) as new information becomes available (Spiller et al., 2015). This has an advantage over the traditional single-stage design where an intervention is fixed for the entire planning horizon, which can result in an under- or over-designed WDN. Huang et al. (2010) address the problem of the optimal design of WDNs in stages that takes uncertainties of future water demand into account. They developed flexible solutions but used a single-objective model for cost minimization. Creaco et al. (2015) investigate three distinct approaches to phasing (or staging) the design of WDNs while also considering a minimum cost objective. Creaco et al. (2014) also propose an approach for phasing the construction of WDNs considering two objectives, the minimization of costs and the pressure surplus. Their solution uses a multiobjective genetic algorithm and draws some comparisons with the fixed design solutions, which shows that the staged design is better. Basupi and Kapelan (2015a) and Basupi and Kapelan (2015b) propose a different approach to develop flexible solutions, taking demand uncertainty into account by applying staged interventions in the network and considering a two-objective model. The model that minimizes cost and maximizes resilience was solved by an NSGA-II algorithm. Marques et al. (2015a) include the flexible WDN design problem with a two-objective optimization formulation involving the minimization of costs and pressure deficits. Marques et al. (2017) solved a three-objective optimization problem by minimizing costs, carbon emissions and pressure deficits. Both studies used a simulated annealing algorithm to solve the optimization problem.

The analysis of literature on WDN and on several other fields, when there are many objectives at stake, shows the ineffectiveness of the Pareto dominance relation in high-dimensional space. In fact, the performance of the Pareto dominance-based algorithms developed for solving problems involving two or three objectives decreases considerably as the number of objectives increases. Various Multiobjective Evolutionary Algorithms - MOEAs (NSGA-II, PAES, MOEA/D-PBI, etc., as presented in Jiang and Yang, 2017), and Multiobjective Simulated Annealing Algorithms - MOSAs (SMOSA, PDMOSA, WDMOSA, etc., as presented in Suman and Kumar, 2006, Bandyopadhyay et al., 2008 and Sengupta and Saha, 2018), developed in the past face severe scalability issues (Jiang and Yang, 2017; Sengupta and Saha, 2018). Many-objective optimization poses new challenges, such as the increasing proportion of non-dominated solutions and the inadequacy of Pareto dominance to create enough selection pressure in problems with a higher number of objectives.

To emphasize the difference between the needs for solving problems involving more than three objectives, a new term "many-objective optimization problems" (MaOPs) has appeared in the literature (Farina and Amato, 2002; Purshouse and Fleming, 2003, 2007). Since Chand and Wagner (2015) established that at least three objectives are needed for a problem to be considered an MaOP the concept has gained widespread popularity (Li et al., 2015; Jiang and Yang, 2017; Sengupta and Saha, 2018).

This paper proposes a many-objective optimization model for the design of WDNs that can be expanded over the planning horizon. The literature shows that the four objectives considered in this work can significantly influence WDN design. However, no research has yet examined the trade-offs between these four objectives (minimizing pressure deficits, undelivered demand, costs and carbon emissions) while also considering a multi-stage design for WDNs to tackle uncertainty issues and, as such, define flexible solutions. Therefore, it is important to address this research gap by understanding the compromises that can be achieved between these objectives to better inform utility decision makers. A scenario-based approach is proposed to deal with uncertain future circumstances by considering a planning horizon that consists of a number of construction stages during which new urban areas can be established over time. Only the design for the first stage of the planning horizon has to be implemented at the time of decision making. However, the scenarios for the future staged development are essential to provide flexibility (de Neufville and Scholtes, 2011) so that the first stage solution can cope with a range of possible future conditions. As an adaptive scheme is implemented, the whole process can be repeated at the end of each stage when more plausible future scenarios can be investigated.

Solving a four-objective and multi-stage design problem is a major challenge for optimization algorithms as it involves exploring a large solution space and comparing many solutions during the optimization process. This complexity increases significantly when a staged design (one that is carried out in stages using short time steps at each stage) is considered under uncertain futures (Mala-Jetmarova et al., 2018). Another challenge is extracting information from a large number of non-dominated solutions found on the approximation to the Pareto front.

The model developed in this paper is solved by an enhanced simulated annealing algorithm, based on the concepts presented in Kirkpatrick et al. (1983), and exploring the amount of domination concept (Bandyopadhyay et al., 2008) capable of overcoming the major drawbacks of scalability previously mentioned.

The remainder of the paper is organized as follows. In section 2, the optimization model is formulated, and section 3 details the optimization tool used to solve the many-objective model. The case study, the results and discussion are presented in section 4 and, finally, the last section sets out the conclusions.

## 2. Multi-stage and many-objective model

The proposed many-objective model can solve problems in urban areas that are expanding through population growth, by exploiting adaptable WDN design over a planning horizon. Efficient interventions for a number of scenarios (represented by different decision paths that can be followed over a planning horizon) need to be defined. A flexible design through a staged scheme is implemented. The staged design means that the WDN constructed can be adapted in future stages as new information becomes available. Therefore, the chosen solution must satisfy design requirements for the first stage and to be prepared to cope with increasingly uncertain future scenarios. The model considers four different minimization objectives, which are, pressure deficit, undelivered demand, total costs and carbon emissions. The objective function (1) is used to minimize the pressure deficit that can occur in future stages:

$$PD = \sum_{s=1}^{NSC} \sum_{t=2}^{NTI} \sum_{n=1}^{NNS} \underset{d=1,\ldots NDC}{Max} \{Max\,[0;\,(\mathrm{Prq}_{\min,n,d} - P_{n,d,t,s})]\}. \tag{1}$$

This pressure deficit (*PD*) is the sum of the pressure deficits, considering all scenarios (*NSC*), all time stages (*NTI*) after $t = 1$, all network nodes (*NNS*) and the maximum deficit for all demand conditions (*NDC*). For $t = 1$, nodal pressures ($P_{n,d,t,s}$ = pressure at node $n$ for demand condition $d$ for time stage $t$ and in scenario $s$) have to be fully satisfied, i.e., nodal pressure must be equal to or higher than the minimum required pressure. In future stages, it is possible for pressure to be lower than this pressure ($Prq_{min,n,d}$ = minimum required pressure at node $n$ for demand condition $d$) but they should always be higher than zero. This is achieved by including the minimum pressure constraint (2) to limit $P_{n,d,t,s}$:

$$\begin{cases} P_{n,d,t,s} \geq \mathrm{Prq}_{\min,n,d} & t = 1 \\ P_{n,d,t,s} \geq 0 & t > 1 \end{cases} \forall\, n \in NNS\,; \forall\, d \in NDC;\, \forall\, s \in NSC. \tag{2}$$

Under pressure deficient conditions, demand cannot be totally met and therefore the supply delivered to nodes is lower than the required demand. A pressure driven hydraulic simulator EPANETpdd (Morley and Tricarico, 2008) is used to simulate hydraulic conditions in the network by using the head-flow relationship proposed by Wagner et al. (1988). The supply delivered (*Ddl*) is obtained for each node by using the expressions in (3) (Wagner et al., 1988), which considers three different conditions:

$$\begin{cases} Ddl = Drq \quad \text{if} \quad P_{avl} \geq P_{rq} \\ Ddl = \left(\frac{P_{avl} - P_{\min}}{P_{rq} - P_{\min}}\right)^{1/2} \times Drq \quad \text{if} \quad P_{rq} > P_{avl} > P_{\min}. \\ Ddl = 0 \quad \text{if} \quad \mathrm{P}_{avl} \leq P_{\min} \end{cases} \tag{3}$$

If the available nodal pressure ($P_{avl}$) is equal to or higher than the required pressure ($P_{rq}$), all the demand required (*Drq*) is satisfied. For nodes with heads between required pressure ($P_{rq}$) and a minimum nodal pressure ($P_{\min}$) the supply is partially delivered and is computed according to (3). No supply will be delivered to nodes with pressures below or equal to minimum nodal pressure ($P_{\min}$). The main purpose of WDNs is to deliver water in sufficient quantity, of required quality and with enough pressure. Expression (1) is used to minimize pressures lower than a required level. But this is not the situation that best guarantees the minimum undelivered water in the WDN. For pressures lower than required, the demand delivered is given by the expression proposed by Wagner et al. (1988), which uses a nonlinear relationship between available pressure ($P_{avl}$) and supply delivered (*Ddl*). In real systems, due to spatial variability of demand, undelivered will also vary even for the same pressure deficit. Therefore, a second objective function, given by (4), is used to minimize the undelivered demand (*UD*) at nodes where the pressure is lower than the required pressure:

$$UD = \sum_{s=1}^{NSC} \sum_{t=2}^{NTI} \sum_{n=1}^{NNS} \underset{d=1,\ldots,NDC}{Max} \{(Drq_{n,d,t,s} - Ddl_{n,d,t,s})\}\,. \tag{4}$$

The undelivered demand is computed from the pressure-driven hydraulic analysis by summing, over all scenarios, all stages after $t = 1$ and all network nodes, the maximum undelivered demand for all demand conditions. In (4), $Drq_{n,d,t,s}$ = demand required at node $n$ for demand condition $d$ for time stage $t$ and in scenario $s$ and $Ddl_{n,d,t,s}$ = supply delivered at node $n$ for demand condition $d$ for time stage $t$ and in scenario $s$.

The objectives of minimizing pressure deficits and undelivered demand are correlated as the supply of a node is driven by the pressure under deficient pressure conditions. However, network designs that only consider the pressure deficit objective will disregard the flow delivered at each node. For example, it is possible for different undelivered demand values to be experienced for the same pressure deficits distributed at a number of nodes. This can be due to the network nodes having different demands even when the pressure deficit is the same, e.g. a pressure deficit of 10 m at a node with demand of 60 L/s has an undelivered demand value that is different from that at a node with demand of 10 L/s but with the same pressure deficit of 10 m. This also means that the undelivered demand minimization objective could be redundant (relative to the pressure deficit minimization objective) when dealing with hypothetical networks with the same demand for all the network nodes, but it is of critical importance to consider it if the network under analysis includes nodes with very different demand values (the typical real world situation). In this case, the minimization of undelivered demand is handled in the optimization process by selecting solutions that tend to increase the network hydraulic capacity (e.g. by using large pipe sizes) for supplying the network areas with the highest nodal demands. This is very important because most WDNs have critical nodes that normally experience high demand, such as hospitals and schools. These are often held to be vulnerable users with priority (with low undelivered demand) over less important areas with very low demand. This cannot be done by simply minimizing the pressure deficits, and so this work also includes undelivered demand minimization as an objective of the optimization model.

The other two objectives of the model are the minimization of the total cost (*CT*) and the minimization of carbon emissions (*CE*). The total cost is given as the sum of the initial solution cost to be implemented in the first stage and the future costs computed by summing all possible options (different scenarios are established as options that can be adopted in future stages), starting with the second stage of the planning horizon. The *CE* are also given by summing the emissions of the first stage with a sum of the future carbon emissions of all the possible future options that can be adopted. The *CT* and *CE* objectives are described in detail in the case study section of this work. The many-objective model also includes the usual hydraulic constraints of WDN design optimization models to check for nodal mass balance, to compute the head loss in the pipe.

As mentioned above, this model aims to find flexible development solutions by considering possible alternative decision paths that can be followed in future. These alternatives should be identified in line with future developments and through the involvement of stakeholders. Therefore, the process of selecting future adaptations for the network and the corresponding probabilities is not the aim of this work; its main aim is to show how this approach can be used as a decision support tool to decision makers.

## 3. Many-objective optimization method

A heuristic based on the concept of simulated annealing (Kirkpatrick et al., 1983) is used to solve the four-objective optimization model. The enhanced simulated annealing algorithm appropriate to deal with MaOPs results from embedding the concept of amount of domination as developed by Bandyopadhyay et al. (2008) in the algorithm of simulated annealing presented in Marques et al. (2015b) (updated version of Cunha and Sousa, 1999). The amount of domination concept ($\Delta dom$) between two solutions $S_a$ and $S_b$ is defined in (5) by multiplying the differences in values of the objectives ($O_i$) divided by the objective range ($R_i$), if this difference is other than zero:

$$\Delta dom_{Sa,Sb} = \prod_{i=1,O_i(S_a)\neq O_i(S_b)}^{NOB} \left|\frac{O_i(S_a) - O_i(S_b)}{R_i}\right|. \tag{5}$$

Its use contributes to overcome the previously mentioned drawbacks of scalability due to the restricted use of the Pareto dominance in MaOPs problems. The amount of domination concept is used in this algorithm to compute the acceptance probability in (6):

$$P_{acp} = \exp\left(\frac{-\Delta dom}{T}\right). \tag{6}$$

The acceptance probability (6) is also function of the temperature parameter ($T$). Simulated annealing is based on an analogy with the physical process of cooling a material in a heat bath; it represents the physical process of heating a material up to its melting temperature and then slowly reducing the temperature to obtain a new material with a reinforced structure and the lowest internal energy state. Accepting worse solutions through the Metropolis criterion (Metropolis et al., 1953) is an essential property of simulated annealing that enables a more extensive search by allowing the algorithm to escape from local optima. Therefore, the parameter ($T$) in (6), plays an essential role in the method as it controls the optimization search by slowly reducing the likelihood of accepting worse solutions (with worse values for the objectives) during the exploration of the solution space. Furthermore, the algorithms stops when ($T$) reaches a low level and when there is a low percentage of accepted solutions.

A pseudo-code describing the most important steps of the algorithm is shown in Fig. 1.

The many-objective simulated annealing initializes by loading the WDN data from the EPANET file and by defining the current solution ($S_{curr}$). Then the iterative process starts until stop criterion is met. This iterative procedure generates candidate solutions ($S_{cand}$) that have to satisfy all constraints of the optimization model; a new candidate solution is generated and the four objectives ($O$) of the model are evaluated ($O_1 = PD$, $O_2 = UD$, $O_3 = CT$ and $O_4 = CE$). Then, a process inspired on the on the work of Bandyopadhyay et al. (2008) to deal with many-objectives, is followed by comparing the dominance status between candidate solution and the current solution (the last accepted solution), and, if needed, the solutions stored in the archive. The archive stores the non-dominated solutions found during the iteration search. To determine the $P_{acp}$, the amount of domination ($\Delta dom$) is computed in different forms (using (5)), also according to the dominance status between candidate and current solution and the archive solutions ($S_{arch}$) that dominate candidate solution (Bandyopadhyay et al., 2008). Three different situations (C), as shown in Fig. 1, can occur after comparing the dominance status. If current solution $S_{curr}$ dominates candidate solution $S_{cand}$ than the situation is (C1) and the $P_{acp}$ is computed with $\Delta dom$ given by the mean value of the amount of domination of the solutions $S_{curr}$ and $S_{arch}$ that dominate $S_{cand}$.

In case C1, all objective values determined for $S_{curr}$ are better (lower) than or equal to those for $S_{cand}$ and at least one of the objectives of $S_{curr}$ has a value lower than the value of an objective in $S_{cand}$ (7):

$$\forall\ i \in 1,2,3,4\text{: } O_i(S_{curr}) \leq O_i(S_{cand})$$
$$\text{and } \exists\ i \in 1,2,3,4\text{: } O_i(S_{curr}) < O_i(S_{cand}). \tag{7}$$

In other words, the candidate solution is worse than the current solution. In this case, the candidate solution can only be accepted as the new current solution if the Metropolis criterion (Metropolis et al., 1953) is met. The Metropolis criterion is met when the acceptance probability ($P_{acp}$), given by (6) is higher than a reference probability ($P_{ref}$ = random (0,1)) randomly generated. Therefore, if $P_{acp} > P_{ref}$ the candidate solution is accepted as the new current solution. The purpose of using the amount of domination concept (5) to determine the $P_{acp}$ used in the Metropolis criterion, is to obtain high $P_{acp}$ to solutions with small amounts of domination and low $P_{acp}$ for those with a high amount of domination.

The second situation (C2) occurs when the current solution and candidate solution are non-dominated with respect to each other. In this case is not possible to improve one of the objectives without worsening another one. Three situations can occur in (C2), depending on the domination status between the candidate solution and solutions from the archive. First, at least one of the solutions from the archive dominates candidate solution (C2.1) and the $P_{acp}$ is computed with $\Delta dom$ given by the mean value of the amount of domination of the solutions $S_{arch}$ that dominate $S_{cand}$. Then the candidate solution can be accepted as the new current solution if the Metropolis criterion is met. Second, the candidate solution is non-dominated by any solution of the archive (C2.2), then the candidate solution becomes the new current solution and is added to the archive. In the third situation, the candidate solution dominates at least one of the solutions from the archive (C2.3), and then the candidate solution becomes the new current solution, is added to the archive and solutions in the archive dominated by the candidate solution are removed.

Finally, in the third condition (C3), the candidate solution dominates the current solution and the current solution is removed from the archive, if this solution is in the archive. Again, three situations can occur. First, at least one of the solutions from the archive dominate the candidate solution (C3.1) and the $P_{acp}$ is computed with $\Delta dom$ equal to the minimum value obtained by comparing the amount of domination of each of the $S_{arch}$ solutions that dominate $S_{cand}$ with $S_{cand}$. Then the candidate solution is accepted as the new current solution if the Metropolis criterion is met. If not accepted, the current solution becomes equal to the solution from the archive that served to determine $\Delta dom$. Second, the candidate solution is non-dominated by any solution of the archive (C3.2), then the candidate solution is converted to the new current solution and is added to the archive. And in the third situation, the candidate solution dominates at least one of solutions from archive (C3.3) then the candidate solution becomes the new current solution, is added to the archive, and the solutions in the archive dominated by the candidate solution are removed.

The algorithm is repeated for a number of iterations at each temperature until equilibrium is reached (Fig. 1). The iterative process ends when a stopping criterion is met. At the end of the process, the archive is composed of a set of the found non-dominated solutions of the problem. These are usually called Pareto solutions (Pareto, 1896).

When a large number of objectives are considered in the optimization model, a high number of non-dominated solutions can be found and therefore a large archive has to be used. In fact, it saves not only the objective function values of the solutions, but also the values for all decision variables (such as all the pipe diameter sizes) that are associated with the solutions. This requires allocating a considerable amount of computational memory to the optimization process (Bandyopadhyay et al., 2008), which is why the size of the archive has to be carefully defined. Initially, it has to be set large enough to accommodate as much information as possible, bearing in mind the possible future number of non-dominated solutions that can be generated, but simultaneously avoiding dimensionality problems. In general, for the same number of iterations, the time required to solve a many-objective problem is greater than the time required to solve the same problem but with fewer objectives. This is because, during the optimization process of the simulated annealing algorithm, new solutions are generated and compared with the non-dominated solutions found so far and saved in the archive. Since a large number of non-dominated solutions are found in many-objective problems, more time is needed to perform these comparisons and thus more computational time is used than is needed for problems with fewer objectives. The simulated annealing algorithm makes use of a set of parameters that influence the number of interactions of the algorithm and the corresponding computational time required to run the optimization. This means that to obtain solutions for the many-objective problems in a reasonable amount of time these parameters must also be calibrated, considering

```
START PROGRAM
Load the WDN file (EPANET file)
Define current solution (S_curr) and evaluate objective functions
DO until stop criterion met
        Generate a random candidate solution (S_cand) that meets all constraints
        Evaluate objective functions corresponding to candidate solution
        IF current solution dominates candidate solution THEN (C1)
                IF Metropolis criterion met THEN
                        Current solution equal to candidate solution
                END IF
        ELSE IF current solution and candidate solution are non-dominated with respect to each other THEN (C2)
                IF at least one of the solutions from archive dominate candidate solution THEN (C2.1)
                        IF Metropolis criterion met THEN
                                Current solution equal to candidate solution
                        END IF
                ELSE IF candidate solution is non-dominated by any solution of the archive THEN (C2.2)
                        Current solution equal to candidate solution
                        Copy candidate solution to the archive
                ELSE candidate solution dominates at least one of the solutions from archive THEN (C2.3)
                        Current solution equal to candidate solution
                        Copy candidate solution to the archive
                        Remove from the archive solutions dominated by candidate solution
                END IF
        ELSE IF candidate solution dominates current solution THEN (C3)
                Remove current solution from the archive if this solution is in the archive
                IF at least one of the solutions from archive dominates candidate solution THEN (C3.1)
                        IF Metropolis criterion met THEN
                                Current solution equal to candidate solution
                        ELSE
                                Current solution equal to archive solution with minimum amount of domination to S_cand
                        END IF
                ELSE IF candidate solution is non-dominated by any solution of the archive THEN (C3.2)
                        Current solution equal to candidate solution
                        Copy candidate solution to the archive
                ELSE candidate solution dominates at least one of the solutions from archive THEN (C3.3)
                        Current solution equal to candidate solution
                        Copy candidate solution to the archive
                        Remove from the archive solutions dominated by candidate solution
                END IF
        END IF
        IF equilibrium at each annealing temperature is met THEN
                Reduce the annealing temperature
        END IF
END DO
END PROGRAM
```

**Fig. 1.** Many-objective simulated annealing pseudo-code (C1-C3 indicate the three main situations in the process).

the additional complexity of the many-objective problems relative to problems with fewer objectives.

## 4. Results and discussion

### 4.1. Case study

The application of the four objective model is demonstrated on a WDN based on the one proposed by Lansey and Mays (1989), that has been changed to include expansion areas. This is a hypothetical WDN but has similarities to real networks. This network has 55 pipes, 2 identical pumps to transfer energy to the flow from a reservoir with a fixed water level and 27 nodes. The layout of the network is presented in Fig. 2.

To meet urban expansion, three development areas are considered and represented in Fig. 2 by the network areas with orange (DA1), green (DA2) and blue (DA3) hatching. These development areas can be constructed in future stages of the planning horizon, in the wake of the scenarios that are described below. The characteristics of the nodes 1 to 17 and pipes 1 to 34 can be found in Lansey and Mays (1989). The remaining nodes and pipes are included in the development areas with the characteristics defined for this specific analysis as follows: nodes 18, 19, 20, 21 and 24 with elevation 15.3 m; node 22 with elevation 24.4 m; nodes 23, 25 and 26 with elevation of 36.6 m; nodes 18, 19, 20, 21, 22, 23, 25 and 26 with the demand of 12.6 l/s; node 24 with the demand of 31.6 l/s; pipes 35, 37, 38, 39, 41, 43, 45, 48, 49, 51, 52, 53 and 55 with the length of 1,830 m; pipes 36, 42, 44, 46 and 47 with the length of 3,660 m and pipes 40, 50 and 54 with the length of 2,745 m. The commercial diameters shown in Table 1, which are taken from Lansey and Mays (1989), are used for the WDN pipe design. This table shows the unit cost and the carbon emissions for each diameter per unit of length. The carbon emissions are computed by a process proposed by Marques et al. (2015c). The Hazen-Williams coefficient is equal to 120 for all commercial diameters.

The capital cost and the carbon emissions are calculated based on the values in Table 1 and the capital cost of installing pumps in links 56 and 57 (Fig. 2), is computed according to Lansey and Mays (1989). To compute the operating costs (calculated from the pumping energy costs) an energy unit cost of 0.12(USD)/kWh is used and an interest rate of 12% is assumed for the determination of the current value of the

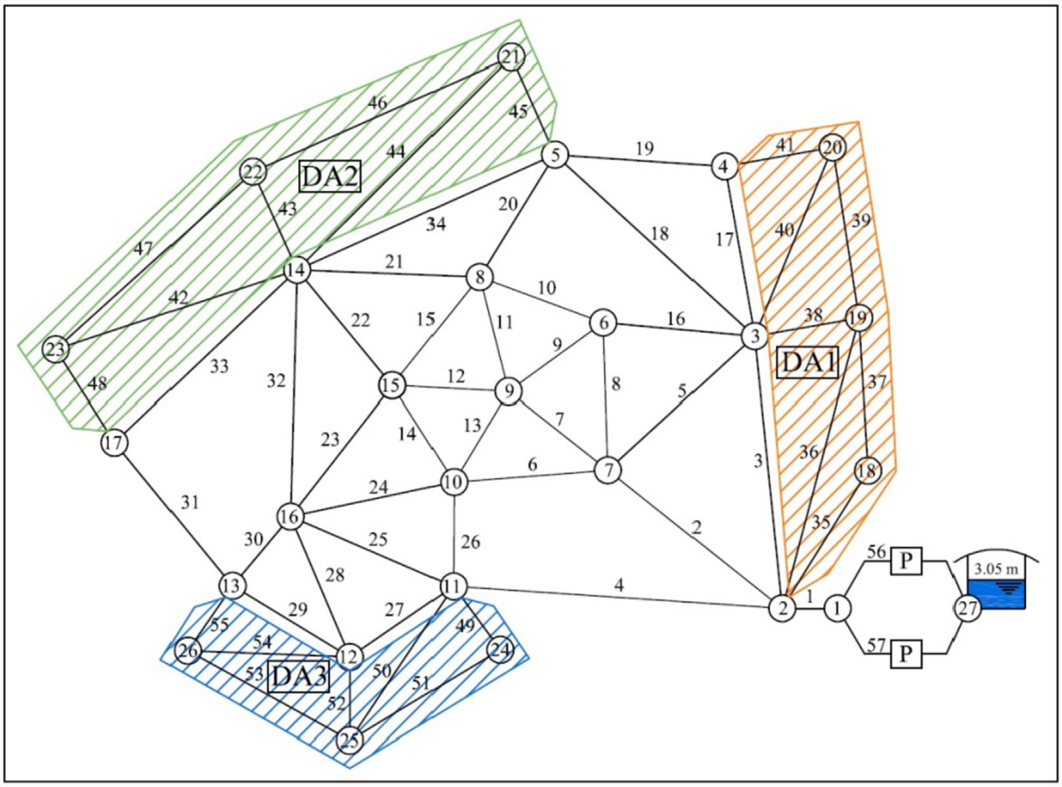


**Fig. 2.** The layout of the water distribution network with three possible development areas.

**Table 1**
Diameter, unit cost and carbon emissions.

| Diameter (mm) | Unit cost (USD/m) | Carbon emissions ($TonCO_2$/m) | Diameter (mm) | Unit cost (USD/m) | Carbon emissions ($TonCO_2$/m) |
|---|---|---|---|---|---|
| 152 | 68 | 0.48 | 406 | 192 | 0.96 |
| 203 | 91 | 0.59 | 457 | 219 | 1.05 |
| 254 | 113 | 0.71 | 508 | 248 | 1.14 |
| 305 | 138 | 0.81 | 610 | 305 | 1.32 |
| 356 | 164 | 0.87 | | | |

costs. The daily water use is divided into four demand conditions of 6 h each, whose value is given by multiplying the nodal demand by 0.67 for the first demand condition from 0:00 to 6:00; by 1.28 for the second demand condition from 6:00 to 12:00; by 1.08 for the third demand condition from 12:00 to 18:00, and by 0.97 for the fourth demand condition from 18:00 to 24:00 (Lansey and Mays, 1989).

As stated, the hatched areas in Fig. 2 represent parts of the city that can be developed in different stages of the planning horizon. To design a network that can be expanded in the future it is advantageous to embed the flexibility perspective from the beginning (or flexibility in systems as defined by de Neufville and Scholtes, 2011). This work takes a planning horizon of 60 years divided into three 20-year stages, when new decisions can be taken. These are organized according to decision paths of options (or scenarios) that can occur over the planning horizon and are detailed in Fig. 3.

In the first stage, a solution must be chosen to be implemented "now", and therefore pipes 1 to 34 (Fig. 2) have to be designed and installed in the initial stage. In the second stage, the authorities are planning to allow urban development in one of the three areas (DA1, DA2 and DA3) of the city shown in Fig. 2, or, if there is no need, maintain the same system (Maintain). In the third stage, the authorities are also planning to allow urban development in an additional area of the city, if such development has occurred in the second stage. If DA1 is installed in the second stage, there is the possibility in the third stage to expand to DA2 or DA3, or Maintain the system. If DA2 is installed in the second stage, expansion to DA1, to DA3 or Maintain are the options. If DA3 is selected in the second stage, expansion to DA1, to DA2 or Maintain are the options. Finally, if Maintain is selected in the second stage, it is admitted that the WDN will again Maintain the system "as is" in the third stage. Each option has associated probabilities to indicate the most probable alternatives that can be taken. For example, the probability to develop areas DA1 and DA2 (0.3) in stage t = 2 is higher than that to develop area DA3 (0.2) or Maintain (0.2) the system. Also, if DA1 is chosen in t = 2, the most probable alternative in t = 3 is to develop area DA2 (0.7), which is close to DA1, and Maintain the system has the lowest probability (0.1). The decisions that are taken under different decision paths establish possible future intervention scenarios in the network, with probabilities given by multiplying the probabilities in that decision path (those that are presented on the right-hand nodes in Fig. 3). These values show scenarios 1 and 4 (probability of 0.21), as the most probable and scenarios 3 and 6 as the least probable (probability of 0.03). In real world applications, these probabilities can be given by expert judgement.

The probabilities of these options are used in the many-objective model to compute the cost objective (8) and the carbon emissions objective (9):

$$CT = Min \quad Cph_1 + \sum_{s=1}^{NSC}\sum_{t=2}^{NTI}\left(Cph_{t,s}\cdot\prod_{kt=2}^{t} prb_{kt,s}\right) \tag{8}$$

$$CE = Min \quad CO_2ph_1 + \sum_{s=1}^{NSC}\sum_{t=2}^{NTI}\left(CO_2ph_{t,s}\cdot\prod_{kt=2}^{t} prb_{kt,s}\right) \tag{9}$$

In (8), $Cph_1$ = cost of the solution to be implemented in the first stage; $Cph_{t,s}$ = cost of future design solutions in scenario $s$ for stage $t$; $kt$ = time stage from $t = 2$ until the stage under analysis and $Prb_{kt,s}$ = probability of scenario $s$ in time stage $kt$. Expression (8) is used

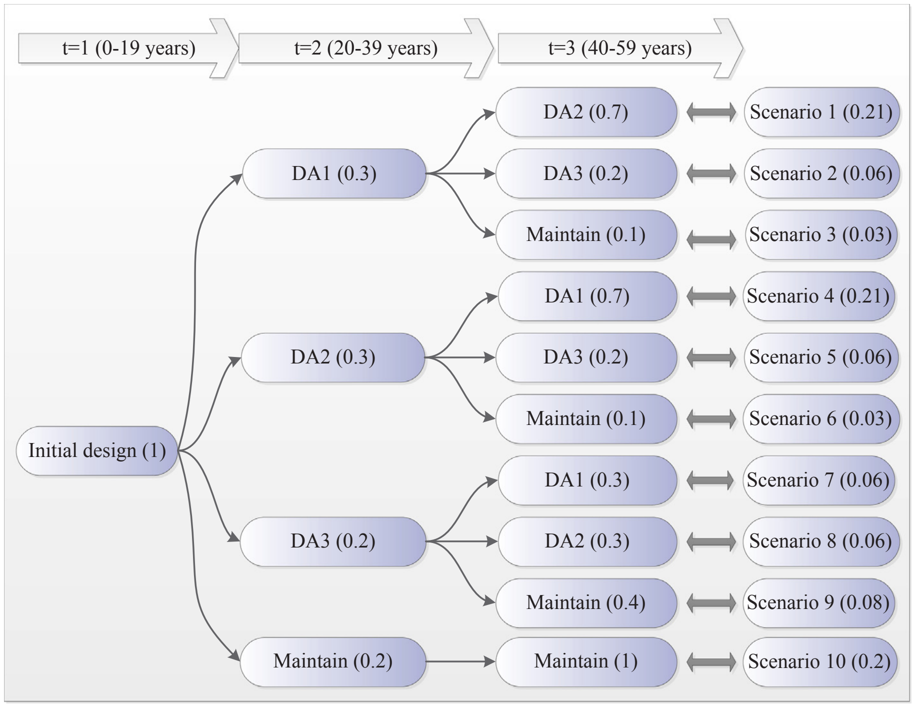


**Fig. 3.** Decision tree for the planning horizon and probabilities of occurrence (in brackets).

to minimize the total cost (*CT*) objective and is given by summing the cost of the initial solution (the first term of (8)) to be implemented in the first stage and the future costs (second term of (8)), computed by a summing of all possible options, starting from the second time stage, given for future stages of the planning horizon. For each option, the costs are computed by multiplying the future cost of each design option by the probability of taking that option. The objective to minimize the carbon emissions (*CE*) is given in (9) where $CO_2ph_1$ = carbon emissions in the first stage; $CO_2ph_{t,s}$ = carbon emissions in scenario *s* for time stage *t*. The carbon emissions are evaluated by the methodology set out in Marques et al. (2015c), which considers the whole life cycle including the extraction of raw materials, transport, manufacture, assembly, installation, disassembly, demolition and/or decomposition. The carbon emissions are given by summing the emissions in the first time stage and by a weighted sum of the carbon emissions in all the possible future options available.

## 5. Results

In a four objective optimization model, it is challenging to extract information from a large number of non-dominated solutions found and from the configuration of the Pareto front. Fig. 4 includes the non-dominated solutions obtained by the many-objective simulated annealing method and were built in the Ahrens et al. (2005) visualization application. The pressure deficit objective is represented using a colour scheme ranging from blue to red, where the pressure deficit ranges from 0 (blue) to 1 (red) and the undelivered demand, total cost and carbon emission are plotted on the *3D* axes of the figure. Furthermore, all four objectives are normalized between (0, 1).

Two distinct parts can clearly be seen in the Pareto front of solutions (Fig. 4). Fronts of this type can occur when the trade-offs between the objectives are dominated by one of them in some region of the solution space. In Fig. 4b) these two parts are highlighted by sets of solutions identified as set S1 in purple, and set S2 in grey. Set S1 consists of a small number of high cost solutions that create a Pareto front that is closer to a curve than a surface in a three-dimensional space. This indicates that in this part of the solution space the trade-off between the objectives (represented in the axes) is controlled by the cost objective. This is because achieving a small improvement in the undelivered demand and pressure deficit objectives in this part of the solution space requires a large increase in the cost objective and a rise in the carbon emissions objective. Therefore, obtaining a solution with a very low or zero undelivered demand, means accepting a costly solution with a very high cost. This is important because it gives decision makers information about a cost threshold level, (in this case, for CT lower than 0.2) above which the undelivered demand and pressure deficit values start to fall at the very low rate. The same conclusion can be drawn for the pressure deficit objective, as in solution set S1 all solution points are the same colour (blue). The other part of the Pareto front, solution set S2, consists of a large number of solutions with low cost objective values and creates a surface in a three-dimensional space.

In addition to the representation of the four-dimensional view (*3D* axes and the colour scheme), the different combinations of two (out of the four) objectives is explored to identify the benefits of using all four objectives. The two-dimensional trade-offs are shown in the next figures by means of dark blue points and lines representing the trade-offs between each combination of two objectives and grey points representing the remaining non-dominated solutions obtained for the four-objective problem.

Fig. 5 shows a clear conflict between cost and undelivered demand (5a). Practically the same format can be seen in trade-offs between cost and pressure deficit in (5b).

Fig. 5 shows how the cost reduction can be achieved with increased undelivered demand and pressure deficit. The trade-off between cost and undelivered demand can be explained as follows. The high cost solutions contain large diameter pipes, which results in networks with high pressure at nodes and thus with low undelivered demand. The differences in the design (decision space) of these solutions can be seen in Fig. 6. This figure details the solutions d1 and d2 marked in Fig. 5a). These two particular solutions have been selected to point out the differences between designs in opposed areas of the solution space. They correspond to scenario 1 (a scenario with a high probability of occurrence) that includes the urban development of DA1 in t = 2 and the urban development of DA2 in t = 3. However, it should be noted that the solutions include all the paths considered in Fig. 3.

In Fig. 6, the pipe diameters (displayed for each pipe) used in d1 are

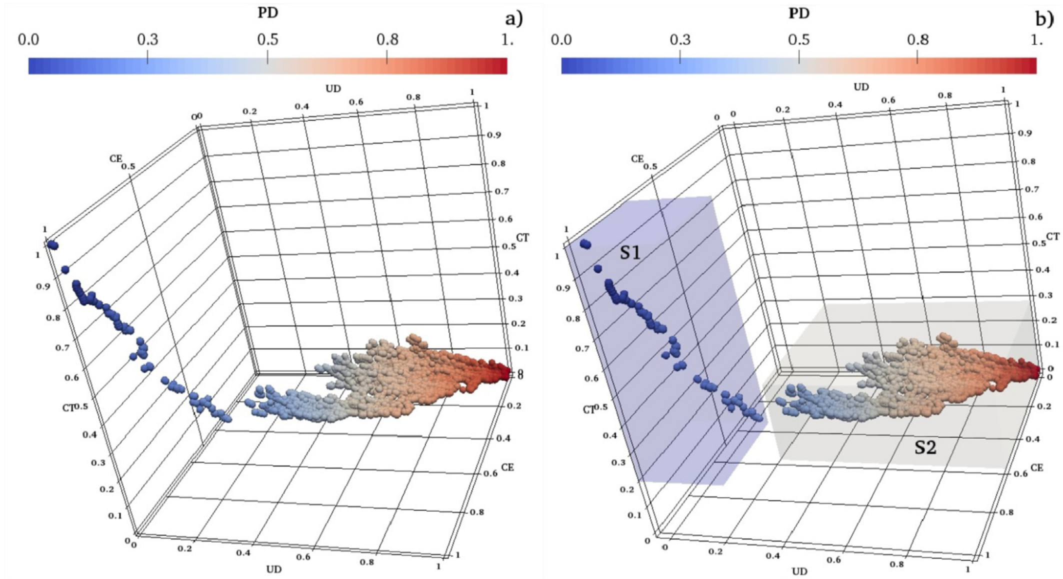


**Fig. 4.** a) Pareto set of solutions b) Pareto set of solutions divided into sets S1 and S2.

larger than in d2, which predominantly contains the minimum possible diameter (152 mm). This increases the total cost objective of (*CT*) from $32 \times 10^7$ (USD) in d2 to $40 \times 10^7$ (USD) in d1. However, the undelivered demand objective (*UD*) is reduced from 1649 L/s in d2 to 202 L/s in d1. Furthermore, the pressure deficit objective (*PD*) is also reduced from 2661 m in d2 to 403 m in d1 by increasing the cost (Fig. 5b).

It is interesting to see in Fig. 7a) that undelivered demand can be reduced from 1 to 0.55 while maintaining low levels of carbon emissions of 0–0.05. The same trend can be seen in (7b), where pressure deficits are related to carbon emissions.

For high undelivered demand solutions, the network pipe sizes are smaller (with high head losses) and pumps have to guarantee minimum pressure requirements and thus have high energy consumption. As network pipe sizes start to increase, the undelivered demand is reduced, however, the carbon emissions remain at the same level because the reduction of carbon emissions related to energy expenditure is offset by the increase in carbon emissions due to the use of high diameter pipes. This can be seen in Fig. 8, which compares the design of solutions d3 and d4 marked in Fig. 7a).

Comparing solutions d3 and d4, the pipe diameters used in d3 are mainly the minimum possible diameter (152 mm), whereas in d4 the pipes have larger diameters which enables a reduction in undelivered demand from 2414 L/s in d3 to 1355 L/s in d4 while the level of carbon emissions is practically unchanged, at $5.5 \times 10^6$ $TonCO_2$ for d3 and $5.6 \times 10^6$ $TonCO_2$ for d4. The same conclusions can be drawn when relating pressure deficits and carbon emissions.

In Fig. 9a) we can see that solutions with the lowest cost also have the lowest values of carbon emissions (solutions near to the graph origin). However, the reduction in carbon emissions is slower for costs above 0.2 and is faster for solutions with costs below 0.2.

Finally Fig. 9b) shows the relation between undelivered demand and pressure deficits. So far, Figs. 5 and 7 do not show any advantage of including both objectives related to the undelivered demand and the pressure deficit. However, Fig. 9b) identifies solutions with similar pressure deficits but with different undelivered demand values. The main advantage of considering minimization of both the pressure deficit and the undelivered demand as objectives is that solutions with lower undelivered demand for practically the same level of pressure deficit can be identified. This can be seen from solutions d5 and d6, indicated in (9b) by diamonds, and which are presented in Fig. 10. Furthermore, to evidence the advantages of considering the undelivered

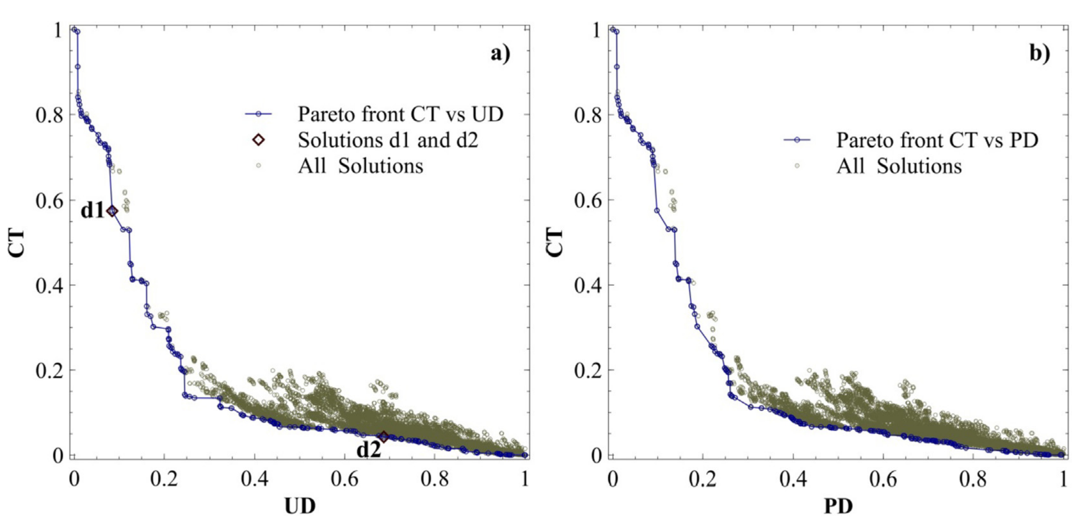


**Fig. 5.** Trade-offs between pairs of objectives. a) CT vs. UD, b) CT vs PD.

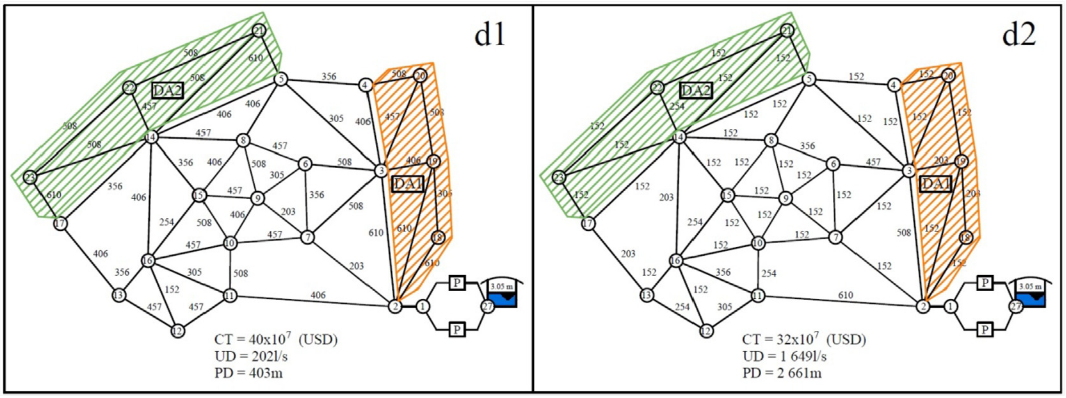


**Fig. 6.** Solutions d1 and d2 for scenario 1 that compare designs and values of CT, UD and PD.

demand as an objective in the model, the same optimization problem was again solved, without considering undelivered demand as an objective but retaining all the other objectives and conditions. One of the solutions obtained without the undelivered demand objective but with practically the same level of pressure deficit as in solutions d5 and d6 is also presented in Fig. 10, as SNUD (Solution obtained with No Undelivered Demand objective). To understand the impact in terms of nodal conditions, these values are presented for the particular conditions of scenario 1.

The designs in Fig. 10 include the pipe diameters of each network link and also the values rounded to units of pressure deficit and the undelivered demand at each node for t = 2 and for t = 3. From d5 and d6 it can be seen that the pressure deficits are practically the same ($PD$ = 165 m in d5 and PD = 167 m in d6) in t = 2 and ($PD$ = 253 m in d5 and $PD$ = 255 m in d6) in t = 3, but the undelivered demand is higher for d5 than for d6 ($UD$ = 114 L/s in d5 and $UD$ = 104 L/s in d6) in t = 2 and ($UD$ = 173 L/s in d5 and $UD$ = 146 L/s in d6) in t = 3. Analysis of the network designs for these solutions makes it possible to conclude that the decrease in undelivered demand offered by solution d6 is attained by the higher capacity introduced in the pipes that supply nodes 9 and 16 with large pipe diameters. These are the network nodes with high demand and, therefore, solutions that cut undelivered demand have to increase the network capacity to supply these nodes. Therefore, solution d6 uses a pipe diameter of 305 mm from node 10 to 9 whereas solution d5 uses the minimum pipe diameter of 152 mm. Also in solution d6, a pipe diameter 508 mm is used from node 11 to node 16, while solution d5 uses 305 mm. With these diameters, the undelivered demand at node 9 falls from 21 L/s to 11 L/s in t = 2 and from 26 L/s to 16 L/s in t = 3. In node 16 undelivered demand falls from 36 L/s to 31 L/s in t = 2 and from 42 L/s to 37 L/s in t = 3, and this is related to the increased hydraulic capacity of the pipes that supply these nodes. From the SNUD solution obtained without considering the minimization of UD as objective in the optimization model, it can be seen that the UD is high even for the same level of pressure deficit in d6, ($UD$ = 128 L/s in SNUD) in t = 2 and ($UD$ = 182 L/s in SNUD) in t = 3. The differences in the design of SNUD and d6 (the solution with the lowest UD values) are mainly related to the lower network capacity in the central part of the city considered in solution SNUD, compared with solution d6, which increases the value undelivered demand value at nodes 6, 7, 9 and 10 in this part of the city.

Comparing the solutions and objectives shows that all four objectives have different trade-offs with one another and consequently formulations without one of these objectives would predispose decision makers towards neglecting potential improvements in one of the objectives relative to the other three. Based on the results from the case study, it is possible to conclude that the solution space has two parts, a curve that indicates the control of the cost objective relative to the others for high cost solutions and a surface part that identifies compromises between all objectives. This work considers a looped network, which is the most common type of real world network. Furthermore, given the energy required to deliver water in this WDN, increasing the pipe capacity not only increases the network reliability (cutting undelivered demand and pressure deficit), it also reduces the energy consumption of pumps by reducing head losses. Therefore, for real water distribution networks with energy expenditure and looped structures, trade-offs between objectives are expected.

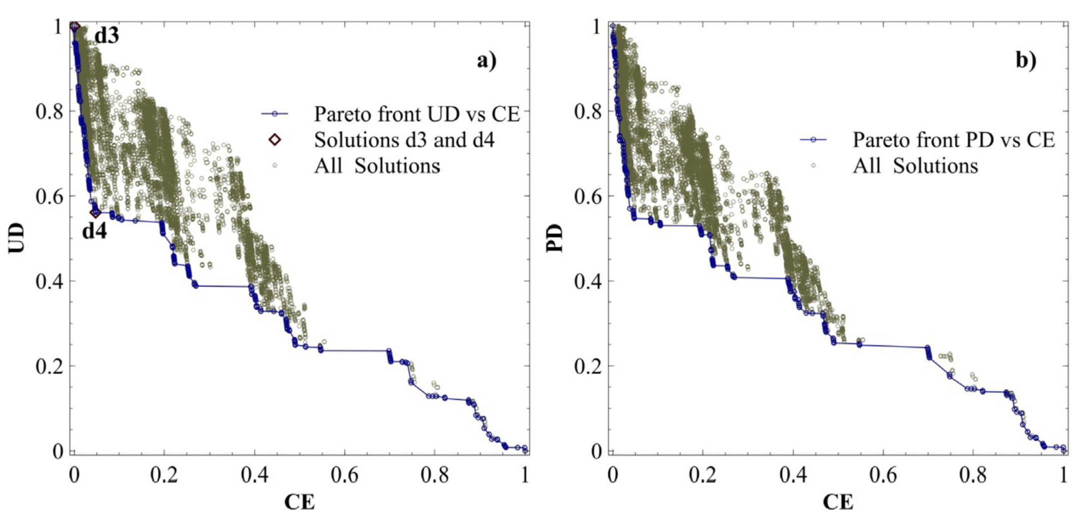


**Fig. 7.** Trade-offs between pairs of objectives. a) UD vs. CE, b) PD vs. CE.

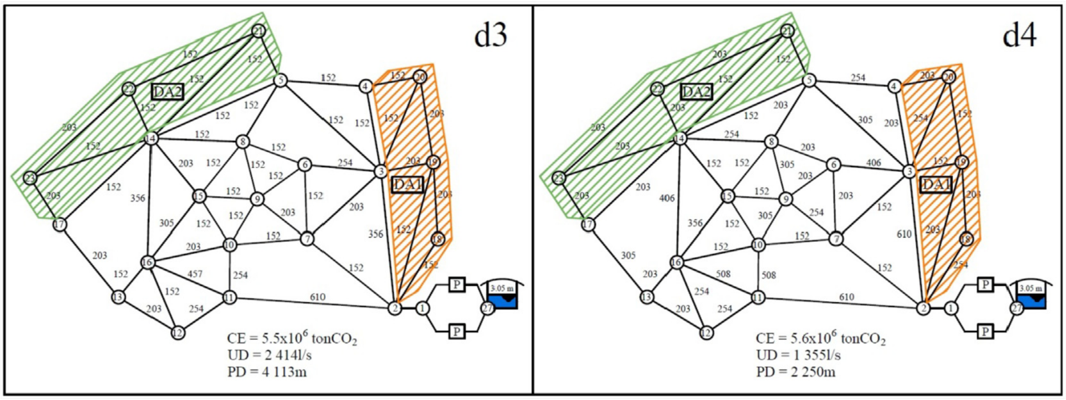


**Fig. 8.** Solutions d3 and d4 for scenario 1 that compare design and values of CE, UD and PD.

## 6. Conclusions

The research set out in this paper was motivated by the interest in solving problems not yet dealt with in the literature: those cast as many-objective problems to develop flexible solutions for the design of a WDN using a multi-stage scheme and including demand uncertainty issues. An enhanced simulated annealing algorithm was developed that is capable of dealing with challenges encountered in MaOPs. Such challenges include handling the ineffectiveness of the Pareto dominance relation in high-dimensional space and the need to create enough selection pressure in problems with a higher number of objectives. The methodology was fully analysed by applying it to a WDN case study for a planning horizon of 60 years, divided into three stages of 20 years. In these stages, different decisions with specific probabilities can be taken according to the different decision paths. The results represent the non-dominated solutions found by the algorithm, including a large number of staged solutions for the design of WDNs. This means that decision makers can select a solution or a small set of solutions to evaluate in more detail. Additionally, they can implement the first stage design without compromising future developments during the planning horizon. Furthermore, various combinations of two of the four objectives are explored to ascertain the benefits of using all four objectives. The objectives considered were the pressure deficit, undelivered demand, cost and carbon emissions. The pressure deficit and undelivered demand objectives were used in the optimization model to incorporate network reliability by evaluating the conditions of insufficient pressure and undelivered demand. The cost objective was used due to the high cost of these systems and carbon emissions were used due to the growing awareness of the implications of climate change.

Analysis of the results leads to some interesting conclusions and demonstrates the relevance of using this approach. The Pareto front is composed of two main parts, one with a low density of solutions which are high in cost, and a second high-density part with low cost solutions represented by a surface. This gives decision makers information about a cost threshold level beyond which the undelivered demand and pressure deficit start to decrease at a high rate. Also, an increase in carbon emissions means that the objectives of undelivered demand and pressure deficit can be reduced. For undelivered demand and pressure deficit between 1 and 0.55, it is possible to keep a very low level of carbon emissions mainly because these solutions, with small diameter pipes, have large operating costs related to the high head losses. As network pipe sizes increase, the undelivered demand is reduced and the carbon emissions remain at the same level, because the increase in carbon emissions due to the use of pipes with high diameter is offset by the reduction of carbon emissions related to energy expenditure. This is demonstrated by showing two solutions with practically the same level of carbon emissions ($5.5 \times 10^6$ $TonCO_2$ in d3 and $5.6 \times 10^6$ $TonCO_2$ in d4) but with different undelivered demand values (2414 L/s in d3 and 1355 L/s in d4).

Finally, this work also identifies the trade-offs between undelivered demand and pressure deficits. The analysis indicates there is the possibility to select more appropriate solutions in terms of undelivered demand or pressure deficits, and therefore the consideration of these two objectives makes it possible to differentiate among these solutions. Comparisons made it possible to identify solutions with different levels of undelivered demand ($UD = 114$ L/s in d5 and $UD = 104$ L/s in d6) in

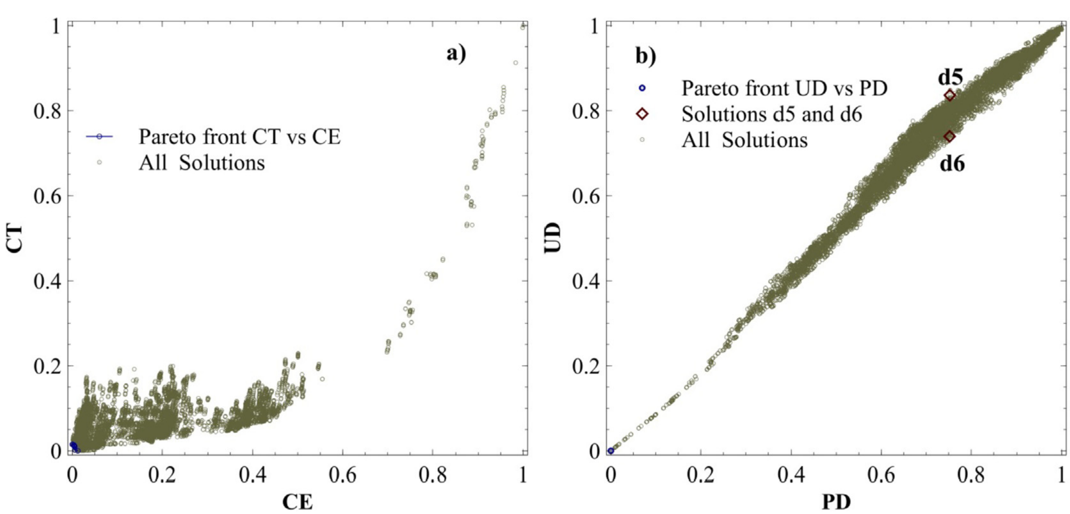


**Fig. 9.** Trade-offs between pairs of objectives. a) CT vs CE and b) UD vs PD.

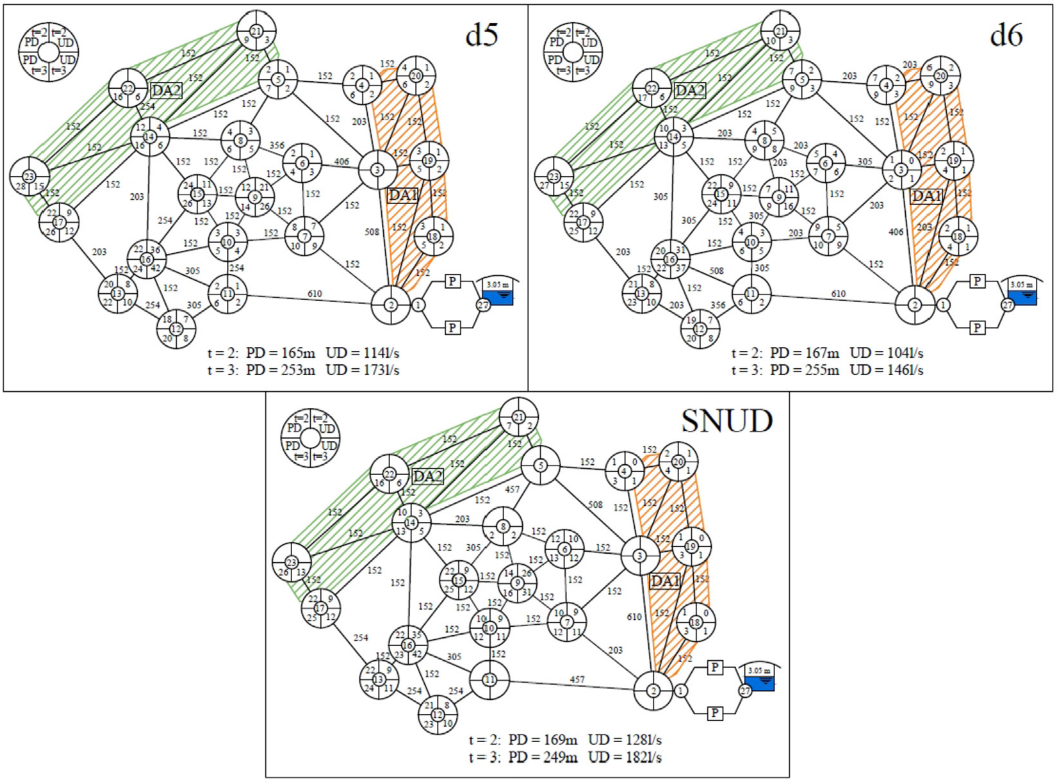


**Fig. 10.** Solutions d5, d6 and SNUD for scenario 1 that compare designs and nodal values of PD and UD for stage t = 2 and t = 3.

t = 2 and with very similar pressure deficit values ($UD$ = 173 L/s in d5 and $UD$ = 146 L/s in d6) in t = 3. These differences are mainly related to the reduction of the undelivered demand at the network nodes with high demand. This is, in fact, an important result as it proves the importance of taking the undelivered demand minimization objective into account at nodes with high demand, which are usually the critical nodes of the network that supply important facilities. For the case study in particular, the analysis of the network designs of these solutions shows that the fall in undelivered demand offered by solution d6 was attained by assigning higher capacity to the network pipes that supply the nodes with high demand.

Additionally, the advantages of considering undelivered demand as an objective in the model were further explored by solving the same optimization problem without considering it. The results clearly show that undelivered demand decreases for the same level of pressure deficit if the minimization of the undelivered demand objective is considered in the model. From the solutions, it is possible to confirm that the undelivered demand increase (for solution SNUD with practically the same level of pressure deficit as in d6) is related to the decrease in network pipe capacity in the areas of the city with the highest consumption of water.

Flexible solutions make it possible to adapt the infrastructure as a function of different scenarios predefined in a decision tree. Each of the solutions obtained for the four-objective optimization model, represents a particular (single) design considering all scenarios of the decision tree. This means that the solution can cope with all pre-established scenarios and thus the idea is not to select a solution for a single optimal scenario but to select solutions that could function as best as possible for a set of different scenarios. A selection of the one (optimal) solution would be difficult as by the very definition of the Pareto set, each solution in it is better in at least one objective than any other solution. In the latter case, a single solution has to be selected by a decision maker in order to be able to implement it.

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## Nomenclature

*CE:* carbon emissions
$CO_2ph_1$: carbon emissions in the first stage; $CO_2ph_{t,s}$ carbon emissions in scenario *s* for time stage *t*
$Cph_1$: cost of the solution to be implemented in the first stage
$Cph_{t,s}$: cost of future design solutions in scenario *s* for stage *t*
*CT:* total costs
*d:* demand condition
*DA:* development area
*Ddl:* supply delivered
$Ddl_{n,d,t,s}$: supply delivered at node *n* for demand condition *d* for time stage *t* and in scenario *s*
*Δdom:* domination
*Drq:* demand required
$Drq_{n,d,t,s}$: demand required at node *n* for demand condition *d* for time stage *t* and in scenario *s*
*kt:* time stage from $t = 2$ until the stage under analysis
*n:* network node
*NDC:* number of demand conditions
*NNS:* number of network nodes
*NOB:* number of objectives
*NSC:* number of scenarios
*NTI:* number of time stages
*O:* objective
$P_{acp}$: acceptance probability
$P_{avl}$: available nodal pressure
*PD:* pressure deficits
$P_{min}$: minimum nodal pressure
$P_{n,d,t,s}$: pressure at node *n* for demand condition *d* for time stage *t* and in scenario *s*
$Prb_{kt,s}$: probability of scenario *s* in time stage *kt*
$P_{ref}$: reference probability
$P_{rq}$: required nodal pressure
$Prq_{min,n,d}$: minimum required pressure at node *n* for demand condition *d*
$R_i$: range of objective *i*
*s:* scenario
$S_a$: solution “a”
$S_{arch}$: solution from archive
$S_b$: solution “b”
$S_{cand}$: candidate solution
$S_{curr}$: current solution
*SNUD:* solution obtained with No Undelivered Demand objective
*t:* time stage
*T:* temperature parameter
*UD:* undelivered demand
*WDNs:* water distribution networks