A DYNAMIC ADAPTIVE APPROACH FOR WATER DISTRIBUTION NETWORKS DESIGN

Maria Cunha[1], João Marques[1], Enrico Creaco[2], Dragan Savić[3]

[1] INESC Coimbra – Institute for Systems Engineering and Computers at Coimbra, Department of Civil Engineering, University of Coimbra, Coimbra, Portugal
[2] Dipartimento di Ingegneria Civile e Architettura, University of Pavia, Pavia, Italy
[3]Centre for Water Systems, School of Engineering, Computing and Mathematics, University of Exeter, United Kingdom.

[1]mccunha@dec.uc.pt, jmarques@dec.uc.pt, [2] creaco@unipv.it [3] D.Savic@ex.ac.uk

Abstract

In the face of a highly uncertain future there is a need for water utilities to develop structured approaches for the long-term strategic design of water distribution networks (WDN). A new conceptual framework for developing an integrative approach based on a multi-criteria decision analysis (MCDA), embracing an optimization model to size flexible alternatives, is proposed. The flexible solutions are evaluated through MCDA for all the criteria (investment costs, carbon emissions, resilience, and reliability of WDNs) across all the scenarios for the sake of robustness and will help to adapt WDN to changing conditions over a long planning horizon, divided into phases. The alternatives are ranked through two different MCDA methods (PROMETHEE and TOPSIS), so that decision makers will have more comprehensive information for analysing highly-ranked design solutions and since the first phase, solutions for the other phases can be reassessed by the same dynamic adaptive framework.

Keywords: Water distribution networks, multiple plausible futures, dynamic adaptive planning, flexible solutions/robustness, phased design, MCDA/PROMETHEE/TOPSIS

1. Introduction

Water infrastructure is characterized by its complex, uncertain and capital intensive nature, which makes it difficult to plan the design and management of its long-lived assets. Water utilities are thus being increasingly challenged to respond to the changing paradigm for dealing with uncertainty issues when planning and managing their asset systems. However, previous approaches to dealing with water problems, which were based on the restrictive assumptions of stationarity, as explained in Milly *et al.* (2008) (of the main variables characterizing water systems) and determinism, as noted in Lempert and Groves (2010) (the use of a single best estimate) for defining management policies or designing infrastructure elements for a long time horizon, are being questioned. The different types of uncertainty, their various definitions and the way uncertainty has been formalized for decision making in different fields can be gleaned from the literature (Roach *et al.* 2016, Watson and Kasprzyk, 2017). Some recent papers (e.g. Maier *et al.* 2016 and Walker *et al.* 2013) have attempted to systematize these aspects and create a common terminology, stressing the need for decision support approaches suitable for situations where there is a lack of information.

Engineers have to make decisions today about water supply infrastructure for future unidentified demand, availability of technology, stakeholder priorities and other unknowns. Indeed, the multiple new drivers of change (climate change, population growth, increasing urbanization, technology developments, socio-economic restructuring, etc.) give rise to innovative approaches for dealing with uncertainty issues to improve the security of water systems. The level of service to be delivered should be defined by exploring multiple plausible futures (the concept as defined in Maier *et al.* 2016) to be well-thought-out in the context of so-called deep uncertainty (Walker *et al.* 2013). A number of plausible futures should come together with robustness and adaptation concepts in decision making. In fact, any strategy to be developed must perform satisfactorily no matter what the future may bring, for the sake of robustness. When it comes to multiple plausible futures, strategies can be developed through adaptive approaches. These will enable the solutions to embrace contingent options to respond to knowledge emerging during the planning period and, as stated in Maier *et al*. (2016), this results in a "collective robustness of the various strategies considered".

In this paper the adaptation strategies are defined through a phased design at fixed time intervals (Maier *et al*., 2016). As such, the traditional approach involving the single-phase design of a WDN is replaced with a multi-phase design, to adapt infrastructure elements to future unknown conditions in stages. Creaco *et al.* (2014; 2015) have already pointed out that this approach provides water companies with a flexible solution so that they can implement short-term construction upgrades while keeping the long-term network growth in view. Sustainable solutions for water distribution networks (WDNs) that take economic, environmental, reliability and societal dimensions into account and assume a wide range of possible futures can only be found by using approaches tailored to deal with the complexity of such management problems. The criteria used in this paper are: investment cost (to take the management of water utilities' limited budgets into account); carbon emissions (to include present environmental concerns related to CO2), resilience, and reliability of WDNs (to ensure a level of WDN performance that meets consumer expectations). The involvement of many actors with conflicting perspectives, including water companies, governments, environmentalists, consumers and financing institutions, is crucial because the decision-making process depends on the input of the different points of view provided by all the stakeholders. Multi-criteria decision analysis (MCDA) can offer a systematic and transparent way to better inform decision making. It can simultaneously encompass a number of different criteria and take into account the priorities set by stakeholders for evaluating design alternatives, for a planning horizon divided into different design phases. This can entail additional challenges when different weights are being assigned to the same criteria for each phase, in accordance with the stakeholders' viewpoint on making, for example, a higher initial investment or delaying investment over the planning horizon or if they take a more risk averse or risk inclined attitude to the performance of the WDN during the planning horizon. Therefore the number of criteria to be evaluated shows a significant increase, because each criterion is disaggregated through the number of phases considered (further discussed in sections 2 and 3, for the application to four criteria weighted differently in four phases). The literature shows that multiobjective approaches (MOs) can be used to solve problems with various objectives. However, only a small number of case studies involving phased design are available. The authors have already considered MOs in previous publications (Marques *et al*. 2015a and Marques *et al*. 2018) and could see the difficulties with obtaining the Pareto front when there are more than three objectives. The literature on many-objective optimization (Chand and Wagner (2015) also emphasizes the difficulties encountered when using standard MOs methods to deal with such problems. In two recent papers by Wang *et al*. 2015 and Wang *et al*. 2017, the comparison of results provided by the best-known multiobjective genetic algorithms showed the sparsity of the Pareto fronts obtained, and how biased they can be. This means that various algorithms could produce Pareto solutions in some parts of the front and had difficulties finding a solution in other parts. Furthermore, the location of densely populated parts of the Pareto front could change from algorithm to algorithm, even when only a two-objective problem was under consideration for WDN design (e.g., resilience and cost). Therefore, in general terms, we can say that using MOs to generate alternatives for a problem where there are many potential criteria (which can also arise when considering a phased design as foreseen in the framework proposed in this paper) could result in only a limited portion of the true Pareto front being identified. This could then invalidate or at least be detrimental to the potential MCDA evaluation of the Pareto solutions found. MCDA can overcome such disadvantages when many criteria are at stake, and also handle specific weights assigned to the criteria in different phases, thus helping to provide decision makers with clear, knowledge-based information.

Therefore, the main purpose of this work was to tackle a very complex problem in a fairly new field, that is: to use a dynamic adaptive approach to define flexible/robust solutions for the phased design of WDNs that take different future scenarios into account, and to do so by exploiting the capabilities of MCDA. This approach will help stakeholders to target short-term issues and select the most flexible/robust solutions across a range of scenarios for a long planning horizon while taking into account several plausible futures. Designers will be able to keep their options open to adapt water network solutions as new information or working conditions become available, through a dynamic adaptive approach. MCDA is valuable when identifying the best ranked network design solutions from a number of systematically built alternatives (subject discussed in section 2.1), considering a set of criteria (subject discussed in section 2.2). There is little likelihood of finding an ideal option to suit all the criteria and so a compromise has to be found. MCDA can consider multiple criteria, as is usual in decision making in this field, and gives insights into understanding how the emphasis given to criteria in specific design phases can influence the determination of the best alternatives.

We can find various works applying different MCDA methods to WDNs. The Preference Ranking and Organization METHod for Enrichment Evaluation (PROMETHEE) was used by Mutikanga *et al*. (2011) for prioritising water loss reduction strategies in a city, Kampala, in a developing country, Uganda. Scholten *et al*. (2014) proposed a Multi-Attribute Utility Theory (MAUT) method to evaluate a set of strategic WDN rehabilitation options related to pipe repair and replacement. Choi *et al*. (2015) prioritized water distribution blocks of pipes in an existing network to be rehabilitated through the ELimination Et Choix Traduisant la REalité (ELECTRE) technique. Gheisi and Naser (2015) applied the Simple Additive Weighting (SAW), the Weighted Product Model (WPM) and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) to select a WDN from a set of layout alternatives with different reliability values given by a measure of statistical flow entropy. Zyoud *et al*. (2016) exploited the Analytical Hierarchy Process (AHP) to prioritize water loss reduction options for a water supply network. Salehi *et al*. (2018) developed a hybrid risk-based decision-making model to prioritize the rehabilitation of WDN pipes in specific zones, according to pipe parameters and TOPSIS was used in the distribution network of Qods, a city in Iran. Liu and Han (2018) offered a methodology for designing district metered areas of WDNs to find the best solution from a set of seven alternatives by a SAW method. Zhou (2018) used a TOPSIS method to prioritize the rehabilitation of pipe groups in WDNs by combining the pipe conditions with their hydraulic significance (as the main or most important pipes). Ismaeel and Zayed (2018) presented a model to assess the performance of WDNs and used PROMETHEE to compute performance indices of the network components. The state of the art in this field shows that there is no literature on the analysis of alternatives for designing new WDNs, considering phased interventions during the planning horizon and thus providing flexible networks that can adapt to new information. A first attempt to tackle these issues, using PROMETHEE, can be found in Marques *et al.* (2017). Some authors have used an integrated MO - MCDA approach to deal with problems in the field of WDNs. Tanyimboh *et al*. (2009) applied a MO algorithm to define the design alternatives of WDNs and an AHP to evaluate these alternative based on the performance criteria of economics and social and environmental impacts. Yazdandoost and Izadi (2016), who used TOPSIS to find the best choice from a set of alternatives given by a Pareto front corresponding to the MO solutions for a WDNs considering a cost minimization and resilience index maximization. Carpitella *et al.* (2018) solved the problem of optimal pump scheduling by using a MO method based on the Non-dominated Sorting Genetic Algorithm II (NSGA-II) presented in Deb *et al*., 2002, to find the non-dominated solutions of the problem and an MCDA analysis resolved by TOPSIS to rank the non-dominated solutions found. In all these works, the number of criteria used in MO is low (two, two and four, respectively). In fact, the main drawbacks mentioned, earlier in this paper, show the difficulty of choosing a list of solutions to be evaluated through MCDA when many objectives are involved, such as when phased designs are being proposed.

Selecting the right MCDA method for a specific analysis is a challenge. Furthermore, there is no unified classification for MCDA methods (Pardalos *et al*., 1995, Figueira *et al*., 2005, and

Cinelli *et al*., 2014). Some authors argue that MCDA methods can provide similar results when the decision problem is well structured and the limitations of the methods are considered (Ashbolt and Perera, 2017). Others (Guarini *et al.*, 2018), however state that the choice of the MCDA method can significantly affect the strength of the results. We have selected two representative MCDA methods with different key characteristics (thus belonging to distinct families) to analyse the type of information that they provide with the results. In fact, this is dictated by the need to provide decision makers with results that have different meanings, so that ranks can be further explored for final recommendations. The classification based on the compensatory or non-compensatory nature of the MCDA methods (Mulliner *et al*., 2016, Banihabib *et al*., 2017, and Danesh *et al*., 2018) is used in the next analysis. Compensatory methods allow explicit trade-offs between criteria, which means that an alternative with some criteria that have poor values can be offset with the good values that it might have for other criteria. Non-compensatory methods are principally based on comparison of alternatives with respect to individual criteria. TOPSIS is a compensatory method and PROMETHEE is a non-compensatory method. While some authors believe that compensatory methods are more realistic than non-compensatory ones, as they neither include nor exclude alternatives made by the threshold values (Greene *et al*., 2011), other authors argue that non-compensatory methods can use preference functions with thresholds (as in PROMETHEE) to eliminate the compensation of very good or bad criteria values which guarantee that each single criterion can play an independent role in the alternative ranking position (Cinelli *et al*., 2014). TOPSIS attempts to choose the alternatives that are simultaneously closest to the positive ideal solution and furthest from the anti-ideal solution (Hwang and Yoon, 1981). The ideal solution is given by the best criteria values for all alternatives and the anti-ideal solution is given by the worst criteria values for all alternatives. A Euclidian distance is used to evaluate the closeness of alternatives to these reference points. These two characteristics enable TOPSIS to intensify the relative significance of alternatives more than other compensatory methods (El Amine *et al*., 2014). Other advantages of this method, according to Velasquez and Hester

(2013) are that it is easy to implement, even in a spreadsheet, and that the number of steps is the same whatever the number of criteria (and in the current study, a high number of criteria is proposed). The main advantages of TOPSIS, according to Roszkowska (2011) and García-Cascales and Lamata (2012), are that it is simple, replicates a similar logic to human thinking when a choice has to be made; best and worst alternatives' performances are evaluated by scalar numbering, a simple mathematical formulation that is translated into good computational efficiency. According to Kabir *et al.* (2014) the weaknesses of this method are mainly related to the required vector normalization in multi-dimensional problems. García-Cascales and Lamata (2012) mention the ranking reversal problems in TOPSIS. However, they also show how to make slight changes in the algorithm to tackle this disadvantage whenever it appears in a case study.

PROMETHEE measures the degree of domination of one alternative over all the others based on pairwise comparisons, and the results are usually represented in an evaluation matrix that displays the ranking of the alternatives. The evaluation of alternatives only requires having enough information to be able to state that one alternative is at least as good as another (Brans *et al.*, 1986). According to Rocco *et al.* (2016) PROMETHEE considers both the advantages and disadvantages of each alternative; it measures the intensity of preference and uses pairwise comparisons to comprehensively analyse the outranking relationships between alternatives. Velasquez and Hester (2013) report that other advantages of this method are that it is easy to use and "does not require the assumption that criteria are proportionate" (i.e. criteria expressed as a percentage). Therefore, this method can handle different kinds of criteria and the direct calculation of the criteria values. However, as stated by De Keyser and Peeters (1996), there is a drawback to PROMETHEE and this is related to the model assumptions: it should only be used if the preference between two alternatives for each criteria can be stated by decision makers and if the differences between the critera of alternatives are significant.

Given that the disadvantages mentioned earlier are not critical when using MCDA to solve WDN design problems, we chose TOPSIS and PROMETHEE from the compensatory and non-compensatory families, also taking these reasons into consideration: the literature shows features of these methods that are appropriate to the aim of the study (considering the typology of problems defined in Guarini *et al.*, 2018) and they received mostly positive comments when analysed in surveys in different areas. As stated by Kittur (2015) for PROMETHEE and for TOPSIS as described in Wang and Chan (2013)), these methods are among the most widely used MCDA methods. This is amply borne out by the extensive literature review (217 papers) by Behzadian *et al.* (2010) on the application of PROMETHEE, and the literature review (266 papers) by Behzadian *et al.* (2012) on the use of TOPSIS is several areas, including water management. Tscheikner-Gratl *et al.* (2017) compare the results of the five methods already mentioned (SAW, AHP, ELECTRE, PROMETHEE and TOPSIS) used to analyse the maintenance and rehabilitation options for an existing, ageing water network. They conclude that SAW and AHP should not be used when too many criteria are involved and propose TOPSIS as a good option since it can handle a large number of criteria while retaining an easy structure. Furthermore, they state that ELECTRE has more ranking differences than the other methods, mostly resulting from ranking reversal problems, whereas PROMETHEE provides generally stable results compared with the other methods. Kolios *et al.* (2016) considered PROMETHEE and TOPSIS to be the most sophisticated (out of six widely used methods SAW, WP, TOPSIS, AHP, ELECTRE and PROMETHEE) and report that they are best at selecting the optimum design of wind turbine support structures. Guarini *et al.* (2018) note that PROMETHEE and TOPSIS are recommended to deal with a large number of criteria and a large number of alternatives (like the MCDA that is to be solved). Widianta *et al.*, (2018) compare the results of SAW, AHP, TOPSIS and PROMETHEE to solve an MCDA problem concerned with an employee placement process, considering five criteria and 60 alternatives. The results show that TOPSIS and PROMETHEE have higher accuracy than AHP and SAW. This is because TOPSIS and PROMETHEE are able to hold many criteria and alternatives, whereas AHP and SAW have low accuracy when too many criteria and alternatives are considered (this study involves five criteria and

60 alternatives). The two methods chosen may allow to explore different ways of ranking alternatives and then provide additional information to stakeholders.

The remainder of this work is organised as follows: section 2 sets out the framework for design WDN under uncertainty, section 3 describes the case study and presents the results, and finally, section 4 closes this work with a presentation of the conclusions.

2. Framework for WDN design under uncertainty

Water distribution networks are long-lived and costly. Pipes installed now remain in service for decades and many can function for more than a century. We use a modern framework to build a flexible decision-aid process to define strategies for designing WDNs, for a lengthy time horizon. A design scheme that considers a planning horizon divided into phases to deal with the uncertain futures states of the world is used. Short-term aims are addressed, keeping options open to allow future actions where needed to achieve long-term goals. As long-term predictions are highly uncertain, this work explores a set of demand scenarios generated for each time phase.

The framework proposed to tackle the problem in question is represented in Fig. 1. A set of scenarios is explored to represent a range of future water consumption demands for a planning horizon divided into phases (*NPH* phases). Then alternatives are sized so that they will be the bases of a flexible approach that allows adaptation if new information becomes available. These designs are obtained by minimizing a cost function considering a set of constraints. Next, as the most innovative part of the methodology, the alternative design solutions obtained, one for each design scenario, are tested through MCDA. To this end, a set of criteria are established to evaluate the performance of each alternative across the multiple scenarios generated. All the information provided by such evaluation, together with the relative importance given to criteria, are the main components for accomplishing a multi-criteria decision analysis. This MCDA will provide the ranking of alternatives, thereby providing decision makers with information on the most robust strategy and allowing them to implement the design for the first phase. If new information becomes available, the solution implemented in the first phase can be reassessed with a view to adapting it, and thus a new robust solution can be determined for the next phase. The procedure can be repeated up to the last phase (last phase starts at *NPH*).

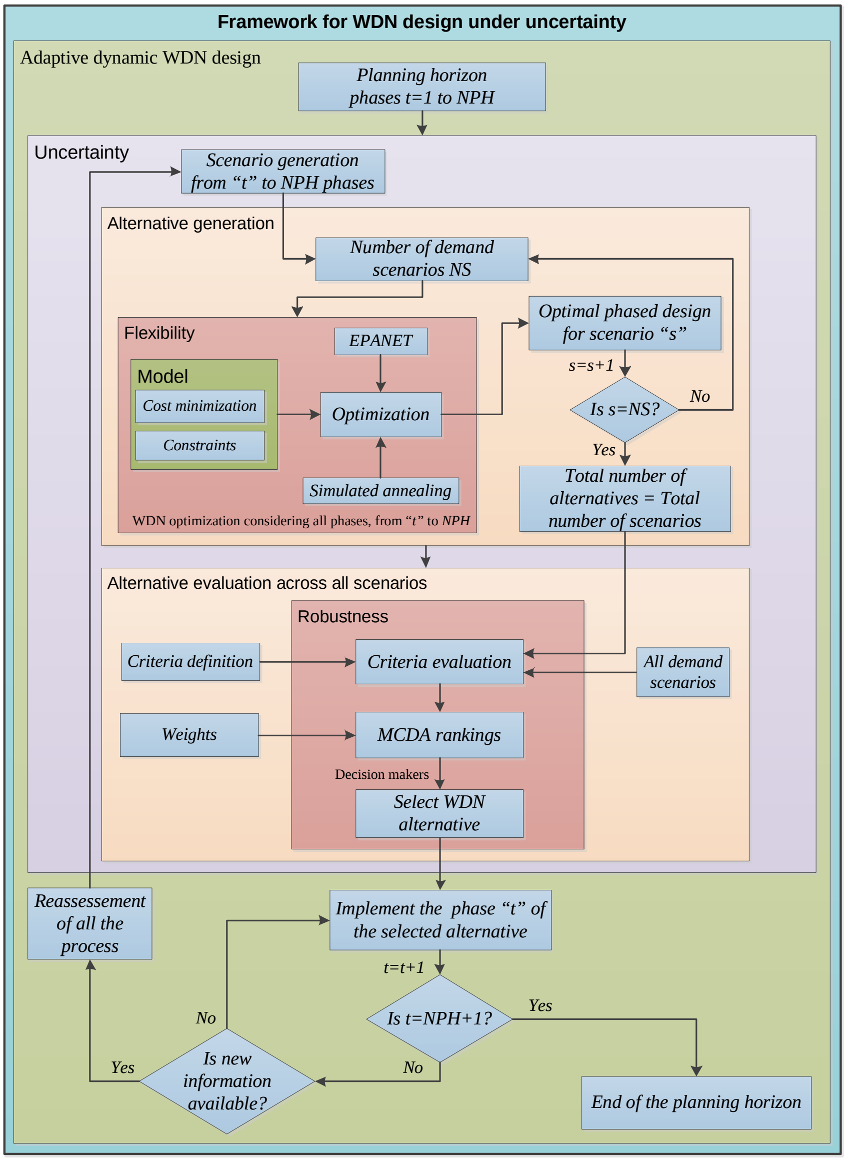

Figure 1: Framework for WDN design under uncertainty

2.1. Alternatives

The definition of alternatives to be evaluated is problem dependent and of paramount importance to the success of MCDA. However, most of the literature on MCDA does not include any explanation on how to tackle this component of the decision-making procedure, with the MCDA description being presented once the problem has been structured (as the rationale of MCDA was simply to evaluate given alternatives). Defining a systematic way for generating alternatives or to identify a suitable, promising and practicable set from a larger number of possibilities is sometimes a challenge. In some problems, alternatives may appear clearly defined, but in others they may be a primary part of the study (Belton and Stewart, 2002). This is really a special issue when matters of compatibility among system components are at stake (Maurer *et al*., 2012). Alternatives representing WDNs fall within this group. In fact, only feasible alternatives from the hydraulic functioning perspective (verifying node and energy equations) are acceptable. Even with a small number of available diameters to size a WDN, including a small number of pipes, the number of diameter combinations is enormous (example: Hanoi network with 34 pipes and 6 possible diameters to size them, presents 2.87×10^{26} different possible network designs (Cunha and Sousa, 1999)). Therefore, when it comes to the question of how to choose from such a big number, a controllable number of alternatives have to be answered. Given the limitation of MO approach to deal a large number of objectives as referred in the Introduction section, a good suggestion appears to be to choose the alternative that, complying with hydraulic equations, offers the least cost and fulfils some pressure requirements. As such compatibility issues are ensured and in fact, no matter what problem is involved, aspects related to cost and pressure would be a concern.

This work uses a range of exploratory scenarios to deal with uncertainty in future demand, through a phased design. Equally probable scenarios are considered in each time phase for the demand, which changes within prescribed bounds (which can result from surveys, from a participatory process, or from the application of elicitation methods). Robustness issues are part of this framework, aimed at dealing with uncertainty, therefore the alternatives to be evaluated must have characteristics that enable them to form the basis for defining those that work well under different demand scenarios. Once again, a systematic approach that simultaneously covers all these issues and generates alternatives is required. Therefore, the alternatives should cover the whole spectrum of the demands generated. Once generated, each alternative will be then evaluated for all the demand scenarios against the criteria proposed (section 2.2). The alternative designs are thus obtained by sizing the network for each of the scenarios, for the sake of the overall robustness performance assessment. Stakeholders can be part of the generation of alternatives procedure.

An optimization model (see Mala-Jetmarova *et al*. 2018 and Maier *et al*. 2014 for a discussion of optimization opportunities and challenges for the WDN design optimization) solved by a simulated annealing heuristic (based on the seminal work of Kirkpatrick *et al*., 1983) is used to size the networks with the objective (*Obj*) of minimizing the investment cost computed according to expression (1). The constraints of the model are represented in (2) to (7).

$$Obj = min\left(CI_{tot}\right) \tag{1}$$

$$H_{n,t,s} \geq H_{min} \qquad \forall n \in NN; \forall t \in NPH; \forall s \in NS \tag{2}$$

$$Dc_{i,t} = \sum_{d=1}^{ND} YD_{d,i,t}.Dcom_{d,i,t} \qquad \forall i \in NPI; \forall t \in NPH \tag{3}$$

$$\sum_{d=1}^{ND} YD_{d,i,t} \leq 1 \quad \forall i \in NPI; \forall t \in NPH \tag{4}$$

$$YD_{d,i,t} \leq YD_{d,i,t+1} \qquad \forall d \in ND; \forall i \in NPI; \forall t \in NPH - 1 \tag{5}$$

$$UD_{t,s} \leq UD\max_{t,s} \qquad t \in NPH \ \wedge \ \mathrm{t} \neq 1 \ \ s \in NS \tag{6}$$

$$UD\max_{t,s} = \sum_{n=1}^{NN} Dd_{n,t,s} \times 0.01 y_t \qquad t \in NPH \ \wedge \ \mathrm{t} \neq 1 \ \ s \in NS \tag{7}$$

Where: *CItot* – total investment cost, for the full planning horizon (USD); *t* – time phase (phase *t=1* starts in year zero); $H_{n,t,s}$ – head at node *n* in time phase *t* and in scenario *s* (m); H_{min} – minimum head (m); *NN*– number of nodes; *NPH* – the number of phases into which the planning horizon is divided; *NS* – the number of demand scenarios; $Dc_{i,t}$ – commercial diameter of pipe *i* installed in time phase *t (mm)*; $Dcom_{d,i,t}$ – commercial diameter *d* assigned to pipe *i* in time phase *t*; $YD_{d,i,t}$ – binary variable representing the use of diameter *d* in pipe *i* for time phase *t*; *NPI* – number of pipes in the network; *ND* – the number of commercial diameters; $UD_{t,s}$ – undelivered demand in time phase *t* for scenario *s* (m^3/h); $UDmax_{t,s}$ – maximum undelivered demand in time phase *t* for scenario *s* (m^3/h); $Dd_{n,t,s}$ – nodal demand at node *n* in time phase *t* for scenario *s* (m^3/h) and y_t – starting year of the time phase *t* (for *t=1* the starting point is year zero $y_1 = 0$) *(years)*.

The investment cost in (1) is detailed in the next subsection. Expression (2) is used to verify the minimum required head at nodes, (3) specifies the use of a set of commercial diameters, (4) assigns one commercial diameter per pipe, (5) specifies the use of the same pipe in future phases after the installation time phase, and (6) limits the amount of undelivered demand (above which the network has to be reinforced).

Expression (7) is used to compute the maximum undelivered demand as a function of the total network demand for a given scenario and y_t (starting year of the time phase t, years). Larger maximum undelivered demand volume is allowed for a later y_t, because of the increased uncertainty of predictions for the long-term relative to predictions for the short term. For the first phase, network pipes have to be installed "now", which means that they should work properly, i.e. satisfy demand in full, for the first phase conditions. However, previous predictions can be reassessed in future phases and therefore the option to reinforce the system can also be re-examined. These maximum undelivered demand values are included in the optimization model to limit the volumes of undelivered demand of the alternative designs. The optimization model makes use of the *EPANETpdd* (Morley and Tricarico, 2008) pressure-driven hydraulic simulator to verify the hydraulic constraints of nodal continuity and head loss in pipes.

2.2. Criteria definition

Criteria to perform the MCDA are defined according to the planning phases. They are conceived to evaluate the investment cost, the carbon emissions and two criteria related to reliability/resilience of the network design, independently for each phase, and the total cost aggregating all investment costs over the whole planning horizon. Therefore, the use of MCDA allows a thorough analysis of all criteria to evaluate the alternatives proposed. The literature shows (a synthesis can be found in Marques et al., 2018) shows the importance of using these criteria for taking into account efficiency of budgets allocation, environmental concerns and performance of networks to meet consumers expectations. The data needed to evaluate these criteria is case dependent and section 3 “Application and results” provides the information for our case study.

The present value of the total investment cost for all time phases is given by criterion (8) and the group of investment cost criteria for each time phase is given by (9).

$$CI_{tot} = \sum_{t=1}^{NPH} CI_t \tag{8}$$

$$CI_t = \sum_{i=1}^{NPI} \left(Cpipe_i(Dc_{i,t}) \times L_i \right) \frac{1}{\left(1+IR\right)^{y_t}} \quad t \in NPH \tag{9}$$

Where: CI_t – the present cost of investment for time phase *t (USD)*; $Cpipe_i(Dc_{i,t})$ – unit cost of pipe *i* as a function of the commercial diameter $Dc_{i,t}$ adopted *(USD/m)*; *Li* – the length of pipe *i (m)* and *IR* – annual interest rate for converting costs to year 0.

The total cost criterion of (8) calculates the investment costs of all the time phases of the planning horizon and (9) computes the present value of the investment cost for year zero (the beginning of the planning horizon) considering pipes to be installed in a time phase, and is given by the commercial diameter unit cost multiplied by the length of the pipe constructed in that phase. The criteria set (10) includes the carbon emissions arising from pipe construction. These carbon emissions are given by the total emissions for all the pipes to be installed in each phase of the planning horizon. The procedure described in Marques *et al.* (2015b) is used to compute the carbon emissions produced by installing pipes in the traditional way, for each of the commercial pipe diameters. The embodied energy emissions are calculated for the whole life cycle and cover the extraction of raw materials, transport, manufacture, assembly, installation, disassembly, demolition and/or disposal.

$$CE_t = \sum_{i=1}^{NPI} \left(CEpipe_i(Dc_{i,t}) \times L_i \right) \quad t \in NPH \tag{10}$$

Where: CE_t – carbon emissions for time phase *t* *(*$TonCO_2$*)* and $CEpipe_i(Dc_{i,t})$ – unit carbon emission of pipe *i* as a function of the commercial diameter $Dc_{i,t}$ installed *(*$TonCO_2/m$*)*.

Two more sets of criteria are used to evaluate the network design for each design phase: the minimum generalized resilience/failure index (*GRF*) proposed by Creaco *et al.* (2016a) and the loop diameter uniformity (*LDU*) used by Creaco *et al.* (2016b). The criteria based on the generalized resilience failure index and on the loop diameter uniformity were chosen because they are related to the issue of network reliability. In fact, the combined use of these two variables represents a surrogate indicator for reliability: a WDN having high values of generalized resilience failure index and loop diameter uniformity is expected to guarantee satisfactory levels of service to users in critical scenarios such as those related to segment isolation and hydrant activation. The GRF_t for each time phase is given in (11) and the annotation used to compute the *GRF* follows the work of Creaco *et al.* (2016a):

$$GRF_t = \min_{s}^{NS}\left(Ir_{t,s} + If_{t,s}\right) \qquad t \in NPH \tag{11}$$

$$Ir_{t,s} = \frac{\max\left(Q^T_{user,t,s} H_{t,s} - Dd^T_{t,s} H_{des,t}, 0\right)}{Q^T_{0,t,s} H_{0,t,s} + Q^T_{p,t,s} H_{p,t,s} - Dd^T_{t,s} H_{des,t}} \qquad t \in NPH, \;\; s \in NS \tag{12}$$

$$If_{t,s} = \frac{\min\left(Q^T_{user,t,s} H_{t,s} - Dd_{t,s}{}^T H_{des,t}, 0\right)}{Dd_{t,s}{}^T H_{des,t}} \qquad t \in NPH, \;\; s \in NS \tag{13}$$

Where: GRF_t – generalized resilience/failure index for time phase t; $Ir_{t,s}$ – resilience index for time phase *t* in scenario *s*; $If_{t,s}$ – failure index for time phase *t* in scenario *s*; $Q^T_{user,t,s}$ – vector ($n_1 \times 1$, and n_1 is the number of junction nodes) to represent the outflow delivered to the users for time phase *t* in scenario *s*; $H_{t,s}$ – vector ($n_1 \times 1$) of nodal heads for time phase *t* in scenario *s*; $Dd^T_{t,s}$ – vector ($n_1 \times 1$) of nodal demands for time phase *t* in scenario *s*; $H_{des,t}$ – vector ($n_1 \times 1$) of desired heads for time phase *t*; $Q^T_{0,t,s}$ – vector ($n_0 \times 1$, and n_0 is the number of source nodes) of water discharges leaving the source nodes for time phase *t* in scenario *s*; $H_{0,t,s}$ – vector ($n_0 \times 1$) of source nodes for time phase *t* in scenario *s*; $Q^T_{p,t,s}$ – vector ($n_{pumps} \times 1$, and n_{pumps} is the number of pumps) of water discharges of pumps for time phase *t* in scenario *s* and $H_{p,t,s}$ – vector ($n_p \times 1$) of pump heads for time phase *t* in scenario *s*.

The *GRF* is given in (11) as the sum of the resilience index and the failure index. The index (12) is based on the original resilience index proposed by Todini (2000) that calculates the ratio of the excess power delivered to nodes and the maximum power that can be dissipated in the network when satisfying the demand. The generalized expression proposed by Creaco *et al.* (2016a) is appropriate for pressure-driven modelling. In (12), the *max* function ensures that only non-negative numbers are obtained for the resilience index. In fact, it is zero when there is a power deficit rather than a surplus. This occurs when the numerator of (12) is less than zero and is unsatisfactory in terms of power delivered to users. The expression (12) always returns values between 0 and 1. The conditions of power deficit are properly taken into account in (13), which computes the failure index. The *min* function used in (13) gets numbers for the failure index that are equal to zero in conditions of power surplus rather than power deficit. The expression (13) always returns values between -1 and 0. A failure index value of 0 means a network without a power deficit and with positive values of *Ir*. A failure index equal to the lowest value, -1, means that no demand is delivered to any network nodes due to the low-pressure conditions. According to this formulation, the indexes *Ir* and *If* can take values different from 0 if and only if one of them is equal to 0. Due to this continuity, Creaco *et al.* (2016a) proposed the *GRF* given by (10) that is used to indicate the power surplus/deficit in networks and that is equal to *Ir* when *Ir* is greater than 0 or is equal to *If* when *If* is less than 0. The GRF_t criteria are obtained considering the minimum GRF_t value for each phase for a set of different demand scenarios under analysis. This means the higher this minimum the higher the reliability.

The last set of criteria is the loop diameter uniformity LDU_t computed for each phase by (14), as proposed by Creaco *et al.* (2016b). This is regarded as a good indirect measure of reliability when combined with network resilience.

$$LDU_t = \frac{n_{pwl,t}}{n_{p,t}} \frac{\sum_{l=1}^{nl_t} C_{l,t}}{nl_t} \qquad t \in NPH \tag{14}$$

$$C_{l,t} = \frac{\sum_{i=1}^{npp_{l,t}} D_{i,l,t}}{npp_{l,t}.\max\left(D_{l,t}\right)} \qquad t \in NPH \tag{15}$$

Where: LDU_t – loop diameter uniformity for time phase *t*; $n_{pwl,t}$ – number of pipes that belong to at least one loop for time phase *t*; $n_{p,t}$ – the total number of pipes in the network for time phase *t*; nl_t – the total number of loops for time phase *t*; $C_{l,t}$ – uniformity coefficient of loop *l* for time phase *t*; $npp_{l,t}$ – the number of pipes in loop *l* for time phase *t*; $D_{i,l,t}$ – the diameter of pipe *i* in loop *l* for time phase *t* and $D_{l,t}$ – maximum diameter in loop *l* for time phase *t*.

The loop diameter uniformity computed in (14) varies according to the pipes added in parallel at network links and with $C_{l,t}$ changing with the pipe diameters. $C_{l,t}$, is calculated in (15) as the ratio of the mean to the maximum diameter of a loop *l* in time phase *t*.

2.3. Ranking alternatives

PROMETHEE (Brans and Vicke, 1985) and TOPSIS (Hwang and Yoon, 1981) are the methods used to solve the MCDA for ranking the alternatives.

PROMETHEE is implemented through the calculation of a ranking index (*Phi*). *Phi* is a number between -1 and 1 that is given by the difference between two preference indexes *Phi+* and *Phi-*. *Phi+* is the positive preference index that measures how much an alternative (*a*) is preferred over the other *N-1* alternatives of the problem, with *N* being the number of alternatives. It is an overall measure of the strengths of an alternative (*a*) and the larger *Phi+* is, the better the alternative. The negative index *Phi-* measures by how much the *N-1* alternatives are preferred over alternative (*a*). It is an overall measure of the weakness of an alternative (*a*) and the smaller *Phi-* is, the better the alternative. The *Phi* index combines the strengths and weaknesses of the alternative into a single score and the larger *Phi* is, the better the alternative.

TOPSIS is implemented through a stepwise procedure and 6 steps have to be followed: first, the decision matrix including the criteria values for each alternative is normalized into a nondimensional matrix to allow comparisons across criteria; second, the normalized values of the matrix are multiplied by the criteria weights; third, the ideal solution that covers all the best attainable criteria values and the anti-ideal solution that contains all the worst attainable criteria values are determined by identifying these values for each criterion from the weighted normalized matrix; fourth, the distance measures of each alternative to these ideal and anti-ideal solutions is calculated; fifth, the relative closeness coefficients *Clc* are determined with these distance measures; and sixth, alternatives are ranked according to the *Clc* in descending order and the best ranked are those with coefficients close to 1. More details about PROMETHEE and TOPSIS can be found in the referenced work.

3. Application and results

3.1. Case study

This study makes use of the skeletonized model of a real network (Hanoi), based on Fujiwara and Khang (1990). This network has a single reservoir, the level of which is constant, 34 pipes to be sized, 3 loops and 31 supply nodes. The layout of the network and the length of the pipes can be found in Fujiwara and Khang (1990) and the Hazen-Williams coefficient is 130 for all diameters. Six commercial diameters are available for the network design (Table 1). The original design assumes a single demand condition for which minimum pressures are required. However, in this study we analysed a set of demand scenarios in a phased scheme.

Table 1. Commercially available diameters

Diameter (mm)	Pipe unit cost (*USD*/m)	Carbon emissions (tonnes CO_2/m)	Diameter (mm)	Pipe unit cost (*USD*/m)	Carbon emissions (tonnes CO_2/m)
305	45.73	0.81	**610**	129.33	1.32
406	70.40	0.96	**762**	180.75	1.59
508	98.39	1.14	**1016**	278.28	2.04

3.2. Scenarios

The set of demand scenarios has been generated for the four design phases. Multiple plausible future trajectories for the change in demand are used. As remarked by Beh *et al.* (2017), the life time of water infrastructures is commonly around 30 to 100 years and thus long term conditions reflecting unknown futures have to be considered for the development of structured staged solutions. As the problem being tackled was taken from the literature, it was assumed that all demand scenarios had the same initial value, which was the same as that in the original case study. Therefore, this was the reference demand for y1=0, while for y2=25 a demand variation between (-5% and +25%) is proposed, for y3=50 the variation is between (-10% and +50%) and for y4=75 it is between (-15% and +75%). Each demand variation for each phase in each scenario is obtained by dividing the demand variation range for the phase into possible discrete values of demand growth and then carrying out a uniform sampling of these values.

A set of 20 demand scenarios are detailed in Fig. 2. The lines connecting the markers are used to help show how the demand develops. Except for three pre-assigned scenarios (indicated in Fig. 2 by black circle icons - scenarios 18, 19 and 20), the other 17 were generated through the procedure described above. In the pre-assigned scenarios, scenarios 18 and 20 are representative of the extreme conditions, that is, constant increase by 25% per phase and constant decrease by 5% per phase. Scenario 19, however, is a conservative scenario with no demand variation in the period and it is represented by horizontally aligned icons.

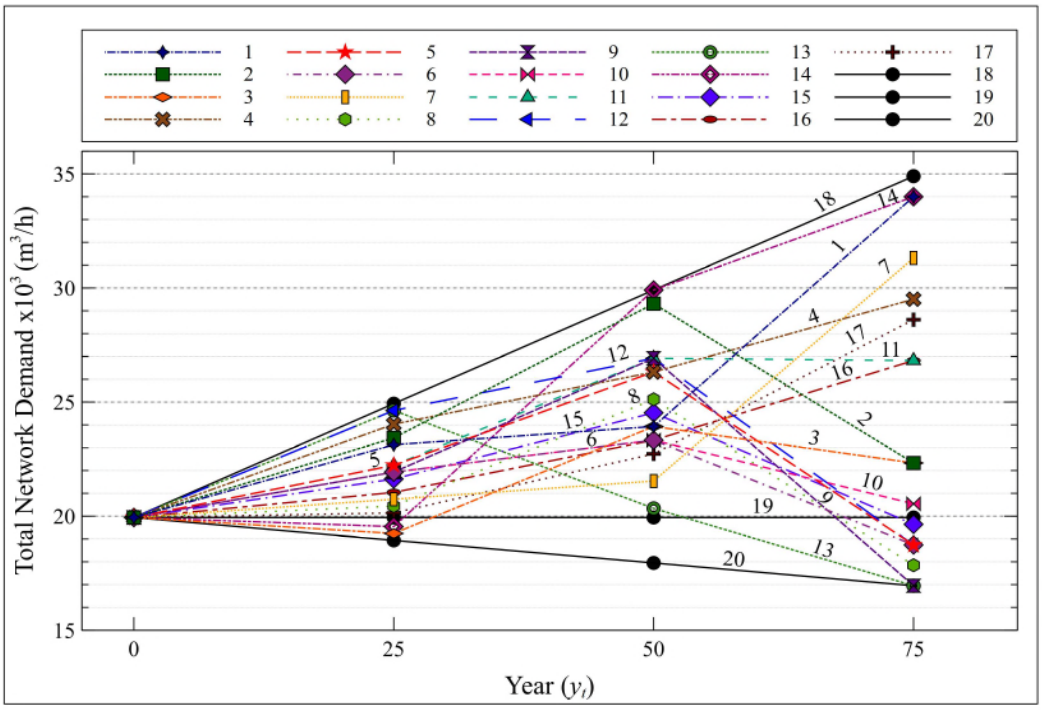

Figure 2: Demand variations for the network with a total base demand of 19.94×10^3 (m^3/h)

The demand variation in all network nodes for each scenario is determined using the percentage of global variation found in each scenario generated. The alternatives were designed based on the assumption that these nodal demands would hold for the 25 years after the implementation year *yt*.

3.3. Network alternatives

Minimum cost solutions were identified using the approach described in section 2.1 for each of the 20 demand scenarios in Fig. 2, considering the possibility of reinforcement with parallel pipes and also respecting the hydraulic constraints verified with EPANET for pressure-driven analysis (Morley and Tricarico, 2008). In the first time phase (t=1), a minimum pressure of 30 m had to be maintained, and in t=2, 3 and 4 the minimum pressure requirement was allowed to be as low as 10 m, but for pressures between 10 m and 30 m the demand was not fully satisfied. These optimized solutions were determined by a simulated annealing algorithm (Marques *et al.*, 2015c) that was linked to the hydraulic simulator.

3.4. Criteria

All the alternative designs were evaluated to assess their performance for the four groups of criteria already defined in section 2.2: investment cost with 5 criteria (total investment cost: CI_{tot}, and investment cost for each phase: CI_1, CI_2, CI_3 and CI_4); carbon emissions with 4 criteria (carbon emissions for each phase: CE_1, CE_2, CE_3 and CE_4); generalized resilience/failure index *GRF* with 4 criteria (*GRF* for each phase: GRF_1, GRF_2, FRF_3 and GRF_4), and loop diameter uniformity *LDU*, also with 4 criteria (*LDU* for each phase: LDU_1, LDU_2, LDU_3 and LDU_4). The investment cost, carbon emissions and loop diameter uniformity criteria were a function of the alternative designs. In the case of the *GRF* criteria, each network design alternative (NDA) was loaded with all the 20 demand scenarios and the minimum *GRF* values of the alternative under analysis were used. The results obtained are given in Table 2 for each NDA, according to the planning horizon phases.

Table 2: Evaluation criteria for the 20 network design alternatives (NDAs)

	Phase *t*=1				Phase *t* =2				Phase *t* =3				Phase *t* =4				
NDA	CI_1	CE_1	GRF_1	LDU_1	CI_2	CE_2	GRF_2	LDU_2	CI_3	CE_3	GRF_3	LDU_3	CI_4	CE_4	GRF_4	LDU_4	CI_{tot}
1	7.12	6.12	0.19	0.58	0.15	0.30	0.35	0.72	0.09	0.45	0.15	0.77	0.24	3.83	0.13	0.90	7.61
2	7.14	6.11	0.20	0.59	0.14	0.28	0.30	0.67	0.21	1.69	0.23	0.81	0.00	0.04	0.04	0.80	7.50

3	6.63	5.87	0.19	0.55	-	-	-0.14	0.55	0.05	0.29	0.09	0.67	-	-	-0.13	0.67	6.69
4	6.92	6.01	0.21	0.62	0.14	0.28	0.32	0.69	0.17	1.25	0.14	0.76	0.11	1.90	0.07	0.88	7.34
5	6.60	5.85	0.18	0.55	0.14	0.28	0.28	0.64	0.12	0.95	0.15	0.80	-	-	-0.03	0.80	6.86
6	6.67	5.90	0.18	0.55	0.14	0.28	0.27	0.64	-	-	0.07	0.64	-	-	-0.17	0.64	6.81
7	6.72	5.91	0.18	0.58	0.14	0.28	0.27	0.66	-	-	0.06	0.66	0.22	3.85	0.09	0.92	7.09
8	7.26	6.17	0.22	0.61	0.11	0.41	-0.05	0.73	0.05	0.28	0.18	0.77	-	-	0.01	0.77	7.42
9	6.97	6.03	0.22	0.61	0.14	0.28	0.35	0.69	0.12	1.19	0.18	0.82	-	-	0.02	0.82	7.24
10	6.73	5.92	0.18	0.56	0.14	0.28	0.27	0.64	-	-	0.06	0.64	-	-	-0.15	0.64	6.88
11	7.05	6.06	0.22	0.60	0.14	0.28	0.34	0.68	0.12	1.04	0.19	0.84	0.03	0.74	0.03	0.84	7.35
12	7.11	6.11	0.21	0.63	0.14	0.28	0.33	0.70	0.09	0.74	0.18	0.81	-	-	0.01	0.81	7.34
13	6.68	5.89	0.16	0.51	0.14	0.28	0.24	0.61	-	-	0.03	0.61	0.00	0.01	-0.21	0.62	6.83
14	7.80	6.41	0.21	0.60	0.15	0.30	0.37	0.73	0.20	1.27	0.24	0.81	0.15	2.42	0.14	0.85	8.30
15	6.79	5.96	0.22	0.63	0.14	0.28	0.33	0.70	0.02	0.17	0.16	0.73	-	-	0.00	0.73	6.94
16	7.37	6.22	0.22	0.60	0.29	0.96	-0.04	0.73	0.05	0.28	0.19	0.76	-	-	0.01	0.76	7.71
17	6.61	5.85	0.19	0.56	0.14	0.28	0.28	0.65	-	-	0.06	0.65	0.14	2.78	0.07	0.83	6.89
18	7.70	6.36	0.22	0.58	0.38	0.74	0.44	0.77	0.12	0.96	0.25	0.77	0.18	2.69	0.16	0.84	8.38
19	6.68	5.90	0.15	0.55	-	-	-0.18	0.55	-	-	-0.44	0.55	0.01	0.21	-0.40	0.62	6.69
20	6.62	5.87	0.17	0.55	-	-	-0.15	0.55	-	-	-0.42	0.55	-	-	-0.57	0.55	6.62

t= Time phase; CI_t= Investment cost x10^6 (USD); CE_t= Carbon emissions x10^4 (Tonnes CO_2); GRF_t= Generalized resilience/failure index; LDU_t=Loop diameter uniformity; CI_{tot}=Total investment cost x10^6 (USD)

At this point, some preliminary analyses can be carried out on the performance of alternative designs. The results show that NDA14 has high investment cost and carbon emission values. This alternative was obtained for a scenario with high demand growth (Fig. 2), and therefore its high hydraulic capacity is due to the use of large pipe diameters in the initial phase and also as a consequence of having to reinforce the network in future phases to satisfy the problem constraints. An initial investment cost of (*USD*) CI_1=7.80x10^6 and future investment costs for parallel pipe reinforcements amounting to (*USD*) CI_2=0.15x10^6, CI_3=0.2x10^6 and CI_4=0.15x10^6 are depicted. It should be noted that the future investment cost is given as the present value computed for year zero. Carbon emissions arising from pipe construction are CE_1=6.41x10^4, CE_2=0.3x10^4, CE_3=1.27 x10^4 and CE_4=2.42x10^4 (tonnes CO_2). These values indicate that in phases t=3 and t=4 the network will require considerable reinforcement. This is because this alternative was obtained for scenario 14, which envisages a very high demand increase in phases t=3 and t=4 (see Fig. 2). The values of *GRF* and *LDU* are also high for NDA14, thanks to the high hydraulic capacity of this design, and thus can perform well for almost all demand scenarios because of the increase in network loops related to the pipe reinforcement with parallel pipes of similar pipe diameter. NDAs 19 and 20, however, with low investment cost and low carbon emissions, have low reliability values of *GRF* and *LDU*. These alternatives were achieved for low or negative demand growth scenarios and therefore have poor hydraulic capacity for functioning in scenarios with demand growth. It should also be noted that as increasing pipe roughness over the pipes' lifetime is considered, the network might have to be reinforced even if demand stays at the same level or declines slightly. For example, NDA19 obtained for scenario 19 with a zero-demand variation, represented in Fig. 2 by horizontally aligned icons, predicts the reinforcement of the network in t=4, as shown in Table 2. This means that this alternative is reinforced in the last phase due to deteriorating network pipes and not because of increased demand.

3.5. Weight sets

An MCDA analysis requires establishing a set of weights to rank alternatives against criteria (weights, in a real-world case study, would represent the relative importance given to criteria by the decision makers). As we are dealing with a phased design, the criteria adopted will have different weights for each time phase and will try to mimic possible common perspectives that can be encountered in real world problems. Four different weight sets (WSs) were used (Table 3). WS1 was established giving a high importance to the cost criterion group (with total weight of 0.6=0.2+0.15+0.1+0.05+0.1), weight of 0.2 to the *GRF* group and low values for carbon emissions and the *LDU* index groups with 0.1 each. The purpose was to give more importance to investment costs and the *GRF* index (but with small magnitude for *GRF*). Furthermore, greater prominence was given to the criteria of the first phases than the last phase criteria. This was because uncertainty increases in the long-term and therefore the first phase criteria should have more weights than last phase criteria. WS1 focused on investment issues. WS2 was established with high importance given to the *GRF* criterion group (total weight 0.6), weights of 0.2 to the investment cost group and 0.1 to the carbon emissions and the *LDU* index groups. WS2 stressed the importance of the reliability measure *GRF*. WS3 was established with the same weight of 0.25 for all criteria groups. Again, WS2 and WS3 favour the first phases' criteria. Just to give an example of the different views of decision makers and their consequences, the same weight of 0.25 was set in WS4 for all groups of criteria but more significance was given to the later phases' criteria than those of the first phase. This can represent a position of risk aversion in an attempt to invest more in the first phases to take advantage of possible additional preparation in these phases, and thereby avoid substantial additional costs in the future if there is a strong belief that changes foreseen in the future will occur.

Table 3: Criteria weight sets

	Phase t=1				Phase t =2				Phase t =3				Phase t =4				
	CI_1	CE_1	GRF_1	LDU_1	CI_2	CE_2	GRF_2	LDU_2	CI_3	CE_3	GRF_3	LDU_3	CI_4	CE_4	GRF_4	LDU_4	CI_{tot}
WS1	0.2	0.04	0.08	0.04	0.15	0.03	0.06	0.03	0.1	0.02	0.04	0.02	0.05	0.01	0.02	0.01	0.1
WS2	0.04	0.04	0.3	0.04	0.03	0.03	0.15	0.03	0.02	0.02	0.10	0.02	0.01	0.01	0.05	0.01	0.1
WS3	0.09	0.12	0.12	0.12	0.07	0.08	0.08	0.08	0.03	0.04	0.04	0.04	0.01	0.01	0.01	0.01	0.05
WS4	0.01	0.01	0.01	0.01	0.03	0.04	0.04	0.04	0.07	0.08	0.08	0.08	0.09	0.12	0.12	0.12	0.05

3.6. Ranking of the alternatives and analysis of results

The values in Table 2 are the basis for performing the MCDA. The ranking of alternatives given by Visual PROMETHEE (Mareschal and De Smet, 2009) and by TOPSIS (programmed in a spreadsheet through the stepwise procedure set out in Behzadian *et al*., 2012), are presented for each weight set, for WS1 and WS2 in Table 4 and for WS3 and WS4 in Table 5. The ranking of alternatives is a function of the *Phi* value in PROMETHEE and a function of the closeness coefficient *Clc* value in TOPSIS.

Table 4: Network design alternatives (NDA) rankings for weights WS1 and WS2

	PROMETHEE WS1		TOPSIS WS1		PROMETHEE WS2		TOPSIS WS2	
Rank	NDA	*Phi*	NDA	*Clc*	NDA	*Phi*	NDA	*Clc*
1	15	0.221	3	0.7540	9	0.305	14	0.8535
2	9	0.119	15	0.7298	15	0.288	9	0.8438
3	17	0.105	6	0.7165	11	0.251	11	0.8417
4	12	0.090	10	0.7161	12	0.232	15	0.8343
5	6	0.084	13	0.7071	4	0.160	12	0.8342
6	11	0.070	8	0.6927	18	0.131	18	0.8325
7	10	0.070	17	0.6919	8	0.122	1	0.8191
8	5	0.066	20	0.6897	2	0.063	4	0.8028
9	3	0.060	19	0.6871	14	0.046	2	0.8027
10	7	0.055	12	0.6724	1	0.020	5	0.7544
11	4	0.048	7	0.6588	16	0.000	17	0.7388
12	13	0.025	9	0.6425	17	-0.007	7	0.7189
13	8	0.004	11	0.6378	5	-0.021	6	0.6881
14	20	0.002	5	0.6337	7	-0.069	10	0.6851
15	19	-0.032	1	0.5946	6	-0.101	13	0.6357
16	1	-0.064	4	0.5659	10	-0.121	8	0.5915
17	2	-0.073	2	0.5534	3	-0.177	16	0.5777
18	16	-0.175	14	0.5296	13	-0.232	3	0.4882
19	14	-0.294	16	0.4679	20	-0.408	19	0.2123
20	18	-0.380	18	0.3692	19	-0.483	20	0.2102

Table 5: Network design alternatives (NDA) rankings for weights WS3 and WS4

	PROMETHEE WS3		TOPSIS WS3		PROMETHEE WS4		TOPSIS WS4	
Rank	NDA	Phi	NDA	Clc	NDA	Phi	NDA	Clc
1	15	0.274	15	0.7530	12	0.163	15	0.8361

2	9	0.207	12	0.7255	15	0.150	8	0.8148
3	12	0.182	17	0.7119	8	0.132	12	0.8012
4	11	0.153	1	0.7091	11	0.128	16	0.7758
5	4	0.150	11	0.7075	9	0.128	9	0.7624
6	8	0.078	6	0.7070	5	0.073	11	0.7588
7	17	0.027	10	0.7052	2	0.054	5	0.7497
8	7	0.027	9	0.7032	4	0.052	10	0.7117
9	1	0.006	7	0.7006	16	0.048	3	0.7093
10	2	0.003	13	0.6837	1	0.021	2	0.7088
11	5	-0.001	5	0.6816	17	0.003	6	0.7023
12	6	-0.038	14	0.6729	7	-0.006	17	0.6744
13	10	-0.039	4	0.6727	14	-0.019	4	0.6709
14	14	-0.095	2	0.6473	18	-0.050	13	0.6661
15	3	-0.107	3	0.6351	10	-0.051	14	0.6523
16	16	-0.117	8	0.5830	6	-0.060	18	0.6511
17	18	-0.138	20	0.5680	3	-0.084	7	0.6019
18	13	-0.147	19	0.5569	13	-0.118	1	0.5994
19	20	-0.194	18	0.5006	19	-0.271	19	0.4893
20	19	-0.231	16	0.3885	20	-0.291	20	0.4455

The comprehensive analysis of solutions provided by the two MCDA methods will help decision makers to explore the rankings with a view to choosing the most appropriate dynamic adaptive scheme to implement, given their priorities. Design decisions in each phase are analysed so that the link to future demand scenarios and the influence of weights are understood.

3.6.1 Best ranked alternatives by PROMETHEE

For WS1, the best ranked alternative of PROMETHEE according to Table 4 is NDA15 and NDA9 is the second best. For WS2, NDA9 is the best ranked and NDA15 is next best. This is because NDA15 includes lower criteria values for investment costs than NDA9, as shown in Table 2 (mainly in phase t=3, NDA15 (*USD*) CI_3=0.02x10^6 and NDA9 with (*USD*) CI_3=0.12x10^6 related to the higher demand increase in t=3 of scenario 9 relative to scenario 15 (Fig. 2)), and in WS1 most importance is given to the cost criteria. In WS2, most importance goes to *GRF* and NDA9 is the best ranked as it includes higher values for the *GRF* criterion group than NDA15 does. For WS3 and WS4, the same prominence is given to all criteria groups, with NDA15 being the best ranked for WS3 and NDA12 the best ranked for WS4 (Table 5). In fact, NDA15 is the best ranked not only when highest weight is given to the investment cost criterion (WS1) but also when the same weight is set for all criteria groups, with the highest weights given to initial phases (WS3). This is because NDA15 includes both low criteria values for investment costs and good values for all the criteria in the first phases. For WS4, that favour the later phases, NDA12 is the best ranked alternative as it includes better criteria values, particularly for *LDU* (NDA12: LDU_3=LDU_4=0.81) than those of the next best ranked alternative (NDA15: LDU_3=LDU_4=0.73).

3.6.2 Best ranked alternatives by TOPSIS

The best ranked alternative for TOPSIS according to Table 4 is NDA3 for WS1, as this has one of the lowest costs and in WS1 this is the most important criteria. In WS2 the most important is *GRF* and the best ranked is NDA14, which is one of the alternatives with the highest values for *GRF* criteria. For WS3 and WS4, NDA15 is the best ranked (Table 5) and in these two weight sets the same importance is given to all criteria, but in WS3 the highest position is given to the first phase criteria and in WS4 the highest importance is given to the last phase criteria. This means that for TOPSIS and for these two WSs, NDA15 includes criteria values that are close to the ideal solution and far from the anti-ideal solution for both first and last phases of the planning horizon. This can be seen in the criteria values of NDA15 presented in Table 2, e.g. the partial investment cost criteria are (*USD*) CI_1=6.94x10^6, CI_2=0.14x10^6, CI_3=0.02x10^6 and CI_4=0. For all four phases, these costs are close to the lowest achievable values of these criteria for all the alternatives (*USD*) CI_1=6.60x10^6, CI_2=0, CI_3=0 and CI_4=0 (used to obtain the ideal solution), and they are far from the worst achievable criteria values for all the alternatives (*USD*) CI_1=7.80x10^6, CI_2=0.38x10^6, CI_3=0.21x10^6 and CI_4=0.24x10^6 (used to compute the anti-ideal solution). This is also true for the other criteria values of NDA15 and therefore explains why NDA15 is the best ranked solution for WS3 and WS4. However, assigning different weights to criteria in different phases, as in WS3 and WS4, has a great impact on the ranking of alternatives that have more satisfactory criteria values in some planning phases than in others. An example is NDA17, which is third for WS3 and twelfth for WS4 in the TOPSIS results. This alternative has a higher rank when significance is given to the first phase criteria (WS3) rather than to those for the last phase (WS4). This is because NDA17 assumes relatively high investment costs (*USD*, CI_4=0.14x10^6) and carbon emissions (CE_4=2.78x10^4 tonnes CO_2) in the last phase of the planning horizon (related to the low demand increase in the first phases (*t*=2 and *t*=3) and a high demand increase in the last phase (t=4) of scenario 17 (Fig. 2)), which reduces the ranking of this alternative if high weights are assigned to the last phase criteria.

3.6.3 Comparison of ranked alternatives by PROMETHEE and TOPSIS

Best ranked alternatives

For WS1 and WS2, the best ranked alternatives by PROMETHEE and TOPSIS are very different (NDA15 by PROMETHEE and NDA3 by TOPSIS for WS1; NDA9 by PROMETHEE and NDA14 by TOPSIS for WS2). The alternatives NDA3 and NDA14 include extreme values for criteria and the best ranked PROMETHEE alternatives (NDA15 and NDA9) are characterized by having good scores for all criteria. In PROMETHEE, each alternative is evaluated over the rest by pairwise comparisons, and thus is less influenced by extreme values of criteria than the TOPSIS method, since TOPSIS tends to improve the ranking of alternatives with very good criteria values of those with the highest weights. This is related with the different nature of these methods. PROMETHEE that is non-compensatory method and therefore no compensation exist in alternatives with very good values of some criteria and very poor values on others. In TOPSIS, that is a compensatory method, this compensation exists and the disadvantages of the values of some criteria can be offset by the advantages of others and if the criteria with advantages have high weights, the corresponding alternative tend to have high ranking positions. However, if the same weight is given to all criteria groups, as in WS3 and WS4, both methods tend to provide similar best ranked alternatives. The results show that for WS3, NDA15 is the best ranked for the two methods and that for WS4 (Table 5), first three ranking positions are filled by the same NDAs, 8, 12 and 15 (but in a different order). This means that, in these weights and for these alternatives, the combined strengths and weaknesses computed in the *Phi* index by the PROMETHEE method (e.g. for WS3, NDA15 has the highest value of *Phi*=0.274) provide similar rankings to those given by the closeness coefficient *Clc*, computed by the relative closeness to the ideal solution in the TOPSIS analysis (e.g. for WS3, NDA15 has the highest value of *Clc*, at 0.753). Thus, these alternatives have similar performance over all the others, for these two methods and for WS3 and WS4.

Other ranked alternatives

Tables 4 and 5 also show that very different rankings of alternatives can be given by PROMETHEE and TOPSIS. This is due to the different structure of the methods. TOPSIS uses distances to the ideal and anti-ideal solutions. This tends to lower the ranking of alternatives when there are very different criteria values compared to the ideal solution, which increases the distance measures and reduces the rankings. For example, in WS1 with higher weights for costs, NDA9 is ranked 2nd in PROMETHEE and 12th in the TOPSIS analysis. These values increase the distance to the ideal solution (solution with the lowest investment cost criteria values) in TOPSIS, which lowers the ranking of NDA9. But the alternatives with very different criteria values from the anti-ideal solution tend to have a higher ranking in TOPSIS than in PROMETHEE. For example, in WS2 with higher weight for *GRF*, NDA14 is in 9th position in PROMETHEE and in 1st position in TOPSIS. This alternative has high weaknesses in PROMETHEE, due to the high cost and high carbon emissions, but in TOPSIS the distance to the anti-ideal solution for the criteria related to *GRF* criteria is low, which improves its ranking. As noted above, in PROMETHEE, each alternative is evaluated over the rest by pairwise comparisons and thus is less influenced by these extreme criteria values. These high weaknesses or low strengths of alternatives are usually associated to the extreme values of criteria. These conclusions are again, related with the different nature of PROMETHEE and TOPSIS and also with its different structure.

3.7. Design solution of best ranked alternatives

The results in Tables 4 and 5 show that there are quite similar groups of best ranked alternatives. Overall, NDA15 occurs in four of the eight best ranked positions and seven times in the best three ranking positions of the analysis by the two methods for the four different WSs. NDA9 occurs four times in the best two ranking positions and NDA12 also occurs four times in the best three ranking positions. These alternatives have a performance that, even using methods from different families and with different weights assigned to criteria, tend to outrank the others and they are thus analysed in detail below. From the decision-making point of view, this kind of comparison and analysis gives additional confidence for selecting appropriate alternatives.

For WS1 with PROMETHEE, for WS3 with the PROMETHEE and TOPSIS and for WS4 with TOPSIS, the best ranked alternative is NDA15. This alternative is achieved for a demand increase of 9 % in t=2, 23 % in t=3 and a demand decrease of 2 % in t=4. The proposed network design includes one pipe reinforcement in t=2 and three pipe reinforcements in t=3, as represented in Fig. 3. This figure shows that in t=2 the link between nodes 2 and 3, which is 1,350 m long and near the reservoir, has to be reinforced with a parallel pipe. The link downstream of the reservoir between nodes 1 and 2 is short (100 m); it is reinforced in t=3, as are the links between nodes 8 and 9 and between nodes 25 and 32. These reinforcements are designed to cope with the demand increase in the relevant phases.

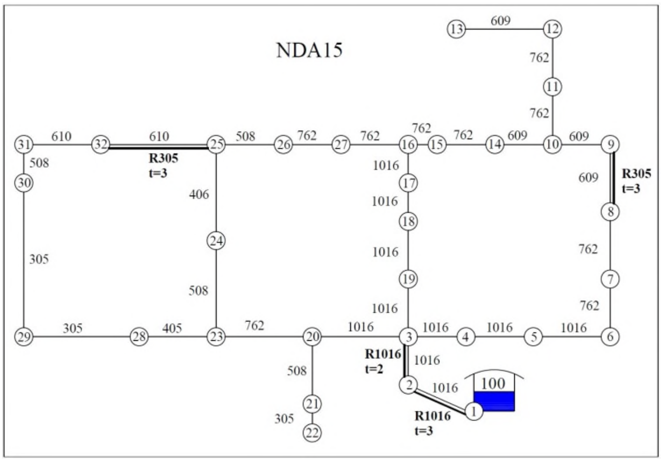

Figure 3: Network design alternative NDA15, including pipe reinforcements in design phases t=2 and t=3, pipe diameters in mm

NDA15 has a relatively low partial investment cost (*USD*) CI_1=6.94x10^6, CI_2=0.14x10^6, CI_3=0.02x10^6 and CI_4=0 and low carbon emissions CE_1=5.96x10^4, CE_2=0.28x10^4, CE_3=0.17x10^4 and CE_4=0 (tonnes CO_2). It should also be noted that the WDN layout includes similar pipe sizes in the network loops that not only give good values for the reliability measures for the *LDU* index (LDU_1=0.63, which is the maximum value of LDU_1 for all the alternatives, LDU_2=0.7, LDU_3=LDU_3=0.73) but also shows good resilience values for the *GRF*, (GRF_1=0.22, GRF_2=0.33, GRF_3=0.16 and GRF_3=0). As Creaco *et al.* (2016b) report, relating *GRF* to *LDU* values lets us identify reliable WDNs and therefore NDA15 seems to be a reliable solution. In WS1, cost criteria have the highest weight and NDA15 is the best ranked solution both because it has low costs and carbon emissions and also because it has high values for the *GRF* and *LDU* criteria. The same conclusion can be drawn for WS3 and WS4, which assign the same weight to all criteria groups, and in fact NDA15 has good values for all criteria, compared with other alternatives.

For WS2 the best ranked alternative is NDA9 with the PROMETHEE method and comes second in the TOPSIS method. This alternative is obtained for a demand increase of 10 % in t=2, 35 % in t=3 and a demand decrease of 15 % in t=4. The proposed network design (Fig. 4) includes one pipe reinforcement in t=2 and 14 pipe reinforcements in t=3. To deal with the high demand growth in t=3, the network undergoes major reinforcement and this increases the investment cost and carbon emissions in the third phase, but it also increases the reliability of the network when it comes to satisfying operating conditions for scenarios with high demand growth. As in WS2, the reliability index *GRF* has high weight, NDA9 is the best ranked because of its high values for *GRF* and *LDU* and average values for cost and carbon emissions.

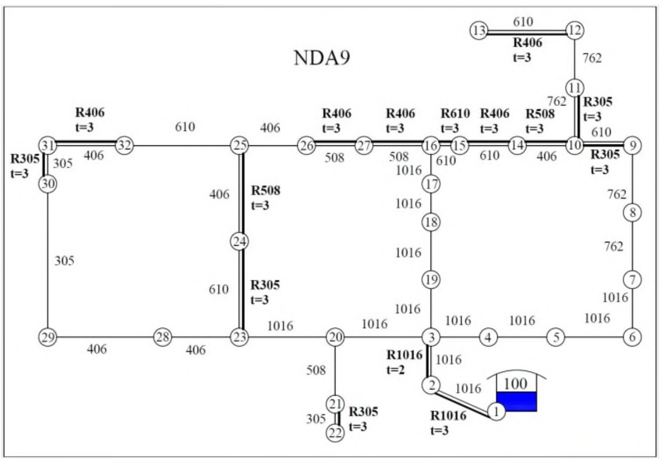

Figure 4: Network design alternative NDA9, including pipe reinforcements in design phases t=2 and t=3, pipe diameters in mm

For WS4 the best ranked alternative is NDA12 for PROMETHEE and it is in third place in TOPSIS. This alternative is determined by a demand increase of 24 % in t=2, 35 % in t=3 and a demand decrease of 6 % in t=4. It is represented in Fig. 5 and includes one pipe reinforcement in t=2 and 11 pipe reinforcements in t=3. NDA9 and NDA12 have similar designs, however, as NDA12 is designed for a higher demand increase in t=2, the first design phases specify large pipe diameters and thus the investment cost is higher than for NDA9. However, this extra network capacity is already in place in future phases and there is no need for as many pipe reinforcement installations as in NDA9. As in WS4, higher weights are given to the later phases and NDA12 has a low investment cost, low carbon emissions and high reliability measures in these phases, NDA12 is the best ranked alternative for this weight set.

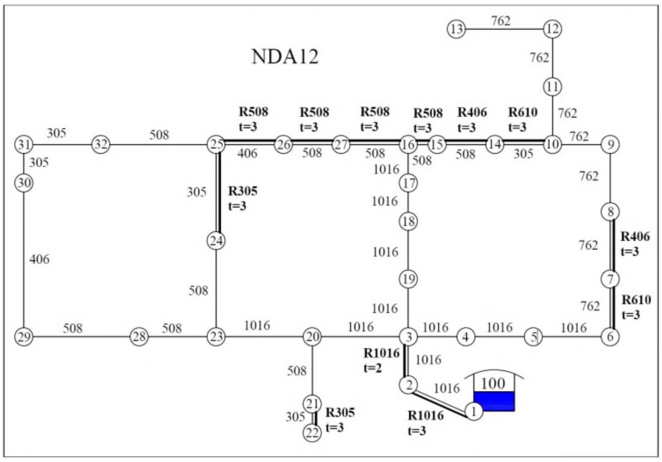

Figure 5: Network design alternative NDA12, including pipe reinforcements in design phases t=2 and t=3, pipe diameters in mm

From these results, it can be concluded that the best ranked solutions (NDA9; NDA12 and NDA15) were designed for scenarios that assumed a demand increase in t=2 and in t=3 and a fall in demand in the last phase, t=4. This means that these network designs are proactively designed and reinforced in the initial phases with enough hydraulic capacity to function for the entire planning horizon. This can also be viewed as an effect of maximizing the resilience measures *GRF* and *LDU* in the multi-criteria analysis since solutions that were proactively reinforced show high resilience for a range of possible future operating conditions.

4. Conclusions

The challenges to be dealt with when planning the provision of a secure water supply are varied, given that so many drivers of change can create multiple plausible futures. It is crucial to cover the conflicting perspectives of many actors when decision-making in such a context. This work proposes a multi-criteria decision analysis (MCDA) as a useful tool to support the identification of the best ranked alternative network designs of new WDNs under uncertainty. These network designs are obtained for different demand scenarios through an optimization model, assuming a phased design scheme that allows the reinforcement of the network in future phases if necessary. This means that flexible alternatives are designed for each phase and their robustness is evaluated across a range of plausible futures. Flexible design and planning is an open field of research. Given the complexity of tackling such problems, a number of different contributions have been identified in the recent literature which explore different methodological approaches that can advance knowledge in this field. The complexities of an unknown future, the limitations, drawbacks and ineffectiveness of previous approaches have paved the way for exploring how such problems are best structured and modelled, and for developing algorithms to tackle them. The structured and intuitive MCDA framework proposed is of great value to supporting a transparent management of public infrastructure elements. It contributes to this area of research by helping decision makers to generate and choose alternatives under conditions of deep uncertainty; it also helps the understanding of the importance of selected criteria. The innovative framework presented in the paper, made up of a combination of multi-phase design and multi-criteria analysis, can be viewed as a dynamic adaptive planning approach. In fact, the results obtained to be implemented at each phase can be reassessed in subsequent phases (making it possible to plan adaptation in advance). When necessary this procedure can be repeated as time goes by as new information becomes available. The design of a new hypothetical network for a planning horizon of 100 years was studied and the analysis proposed 20 alternative network designs covering 17 criteria for the cost, carbon emissions and the hydraulic reliability of the network. The alternatives were ranked using the PROMETHEE and TOPSIS methods for four different weight sets. The results make it possible to explore the influence of weights on the alternative rankings and the different solutions provided by methods from different MCDA families. This gives decision makers additional insight when it comes to selecting the most useful alternatives and discarding the worst ranked ones. The results also emphasize the impact of taking carbon emissions into account in these MCDAs, because if carbon emission criteria are not considered, then alternatives that plan to reinforce the network in the later phases tend to be preferred in the final ranking. The outcomes of this paper are supported by an extensive analysis of results obtained for the aforementioned case study, which represents a step forward in the field of WDN design. This is a new framework for modelling and solving a complex problem, thereby contributing to the body of knowledge whose roots lie in the ideas of "phased design", "flexible solutions", "adapting as new information becomes available" and "deep uncertainty". After the initial but important step made in this paper, many aspects of the framework developed can be further enhanced. For example, exploring different ideas for tackling uncertainty issues, and/or building an improved framework for tackling a problem by embracing so many different issues at the same time. In fact, robustness and flexibility issues can be further developed through scenario analysis, exploring other variants of a systemic approach to dealing with alternative generation. Questions such as pumps, valves, modification/extension of an existing network, the importance given to demand growth in different phases, analysis of the design in each phase and the link to future demand scenarios and the weights influence, modelling issues, and stakeholder involvement in real-world problems are all issues that also need additional reflections in the future. The analysis of the design in each phase and the link to future demand scenarios and the weights influence of weights is also to be further understood.

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