

To be cited as: Marques, J., Cunha, M., & Savić, D. A. (2015). Multi-objective optimization of water distribution systems based on a real options approach. *Environmental Modelling & Software*, 63, 1-13.

Multi-objective Optimization of Water Distribution Systems Based on a Real Options Approach

João Marques¹, Maria Cunha² and Dragan A. Savić³

¹ Departamento de Engenharia Civil, Faculdade de Ciências e Tecnologia da Universidade de Coimbra, Portugal.

² Departamento de Engenharia Civil, Faculdade de Ciências e Tecnologia da Universidade de Coimbra, Portugal.

³ Centre for Water Systems, School of Engineering, Computing and Mathematics, University of Exeter, United Kingdom.

¹jmarques@dec.uc.pt, ²mccunha@dec.uc.pt, ³D.Savic@ex.ac.uk

This paper describes a multi-objective optimization model including Real Options concepts for the design and operation of water distribution networks. This approach is explained through a case study with some possible expansion areas defined to fit different future scenarios. A multi-objective decision model with conflicting objectives is detailed. Also, environmental impacts are considered taking into account not only the life cycle carbon emissions of the different materials used during the construction of the networks, but also the emissions related to energy consumption during operation. These impacts are translated by giving a cost to each tonne of carbon dioxide emitted. This work presents a new multi-objective simulated annealing algorithm linked to a hydraulic simulator to verify the hydraulic constraints, and the results are represented as points on the Pareto front. The results achieved show that the approach can deal explicitly with conflicting objectives, with environmental impacts and with future uncertainty.

Keywords: carbon emissions, multi-objective optimization, real options, simulated annealing, uncertainty, water networks.

1 **1 Introduction**

2 Water distribution networks today are complex systems that require high investment for
3 their construction and maintenance. The storage and transport of water has been
4 extensively investigated in recent decades by applying optimization techniques to water
5 distribution systems design (Sacks *et al.* 1989). In developed countries almost everyone
6 has access to water systems, but several problems remain to be solved such as
7 intermittent supply and the high level of water losses. Furthermore, as urban centers
8 continue to grow so does the amount of water used. The networks have to continually
9 adapt to new circumstances to provide an adequate service.

10 The design of water distribution networks is often viewed as a single-objective,
11 least-cost optimization problem with pipe diameters being the primary decision
12 variables. But when we need to address several objectives, multi-objective optimization
13 can be used to design of water distribution network instead. A number of researchers
14 and practitioners have noted that the optimal design of water distribution systems is a
15 multi-objective issue since it involves compromises between conflicting objectives,
16 such as total cost, reliability and level of service. Savic (2002) demonstrates some
17 shortcomings of single-objective optimization approaches and uses a multi-objective
18 based genetic algorithm (Fonseca and Fleming 1993) to avoid these difficulties.
19 Farmani, *et al.* (2004), Prasad *et al.* (2003), Creaco and Franchini (2012) and Todini
20 (2000) explored the application of multi-objective optimization where the minimization
21 of cost and maximization of reliability are the main objectives. Di Pierro *et al.* (2009)
22 compared two multi-objective algorithms for the design of real size networks. This

23 paper describes the solution of a multi-objective optimization model with two
24 conflicting objectives.

25 This work aims to include the cost of carbon emissions in the design and
26 operation of water networks. We must therefore quantify the emissions from the very
27 beginning of extraction of the different materials used in the water systems until their
28 final disposal. Dennison *et al.* (1999) use life cycle analysis to compare the
29 environmental impact of different pipe materials. Dandy *et al.* (2006) developed a
30 multi-objective model that uses sustainability objectives in life cycle cost analysis,
31 energy consumption, greenhouse gas emissions and resources consumption. The tool
32 compared the minimum cost design with the sustainable environmental design. Herstein
33 *et al.* (2011) presents an index-based method to assess the environmental impact of
34 water supply systems. The index aggregates the consumption of resources,
35 environmental discharges and environmental impacts in a single index. Different
36 materials for tanks, manholes and moorings construction must be used to build up the
37 water supply infrastructure. The most common are: the steel used in pipes, accessories
38 and pumps; reinforced concrete; plastic for pipes and accessories; aggregates for
39 pipeline backfill and asphalt for repaving. The methodology presented Marques *et al.*
40 (2014a) is used to evaluate the carbon emissions involved, considering the whole life
41 cycle including the extraction of the raw materials, transport, manufacture, assembly,
42 installation, disassembly, demolition and/or decomposition. The methodology also
43 computes carbon emissions from the energy used during the network's operation.
44 Adding together the partial contributions of pipe installation and energy consumption it
45 is possible to compute the total carbon emissions. It is also necessary to fix a value for
46 the carbon emissions cost for each tonne emitted. These costs are included in the
47 optimization model presented in the next section.

48 According to Haimes (1998) the great challenge for the scientific community in
49 the third millennium will be to develop tools and technologies to support and maintain
50 infrastructure. Several methods for the effective planning of water systems have
51 appeared in the literature. If flexible planning can be adopted, the infrastructure will be
52 able to cope with future uncertainty. Real options (ROs), originally from financial
53 theory, could make an important contribution in this area. Myers (1977) was the first to
54 introduce the term real options. Since then a large number of studies have been
55 published where the concepts of ROs have been used in several fields.

56 A number of studies have developed ROs approaches to solve a variety of
57 problems: Nembhard and Aktan (2010), who systemized applications of ROs to design
58 and resolve engineering problems; De Neufville *et al.* (2006) report the use of ROs in
59 car parking problems, and Gersonius *et al.* (2010) apply ROs analysis to the option
60 planning process in urban drainage systems to incorporate flexibility to accommodate
61 climate change while reducing future flood risk. In the water industry, an ROs technique
62 appears in the work of Woodward *et al.* (2011) to define maritime coastal defenses to
63 reduce the risk of flooding. In the area of water systems expansion, Suttinon and Nasu
64 (2010) present an ROs based approach where the demand increases. Zhang and Babovic
65 (2012) use a ROs approach to evaluate different water technologies in water supply
66 systems under uncertainty. The work of Creaco *et al.* (2014) proposes a multi-objective
67 methodology aiming at considering the phasing of construction within the design of the
68 water distribution systems, which grow in terms of layout size. The work of Huang *et*
69 *al.* (2010) describes the application of ROs to the design of water distribution networks
70 and Basupi and Kapelan (2013) presents a methodology to the flexible and optimal
71 decision making dealing with future demand uncertainty. Finally the authors have
72 already used ROs in two prior works: Marques *et al.* (2014b) to the optimal design of

73 water distribution systems using a single objective model formulation demonstrated in a
74 simple case study and Marques *et al.* (2014a) taking into account carbon emissions and
75 by using a different single objective model formulation demonstrated in “Anytown
76 network”. Here a new multi-objective optimization tool based on simulated annealing is
77 proposed to solve the multi-objective optimization model based on ROs that
78 incorporates two conflicting objectives explicitly. There is a vast body of literature
79 about multi-objective approaches that have been used in several fields: Hakanen *et al.*
80 (2013) in wastewater treatment plant design and operation; Ahmadi *et al.* (2014) to
81 calibrate of watershed models for pollutant source identification and watershed
82 management; Giuliani *et al.* (2014) to the operation of complex environmental systems
83 and Zheng and Zecchin (2014) for designing water distribution systems with multiple
84 supply sources are just some recent examples.

85 It is very important in water systems planning to predict future operating
86 conditions. However, cities are continually changing and the water supply networks
87 have to be adapted to these changes. Sometimes a new urban or industrial area is built
88 and the network has to be improved to accommodate the new conditions. The opposite
89 can occur in areas where population declines and demand falls. This work presents a
90 multi-objective approach where uncertainty is related to new expansion scenarios for
91 the network.

92 Some benefits of flexible design are associated with the ease of accommodating
93 different future scenarios. However, flexibility usually incurs an extra cost at the initial
94 stage of a water network design. A flexible design is one that enables the designer,
95 developer, or operator to actively manage or further develop the configuration of the
96 system downstream, to adapt it to changes in the supply, demand, or economic
97 environment. The ROs approach presented in this work uses a decision tree to reflect

98 different scenarios that may occur during the planning horizon. The process uses a
99 multi-objective optimization model to find solutions for the first period and for different
100 possible future realities according to the decision tree. The model uses two objectives: a
101 minimum cost objective function that takes into account the carbon emission costs and a
102 level of service measure that minimizes the pressure failures that can occur over the
103 entire planning horizon. Various scenarios are analyzed to predict different alternative
104 future conditions.

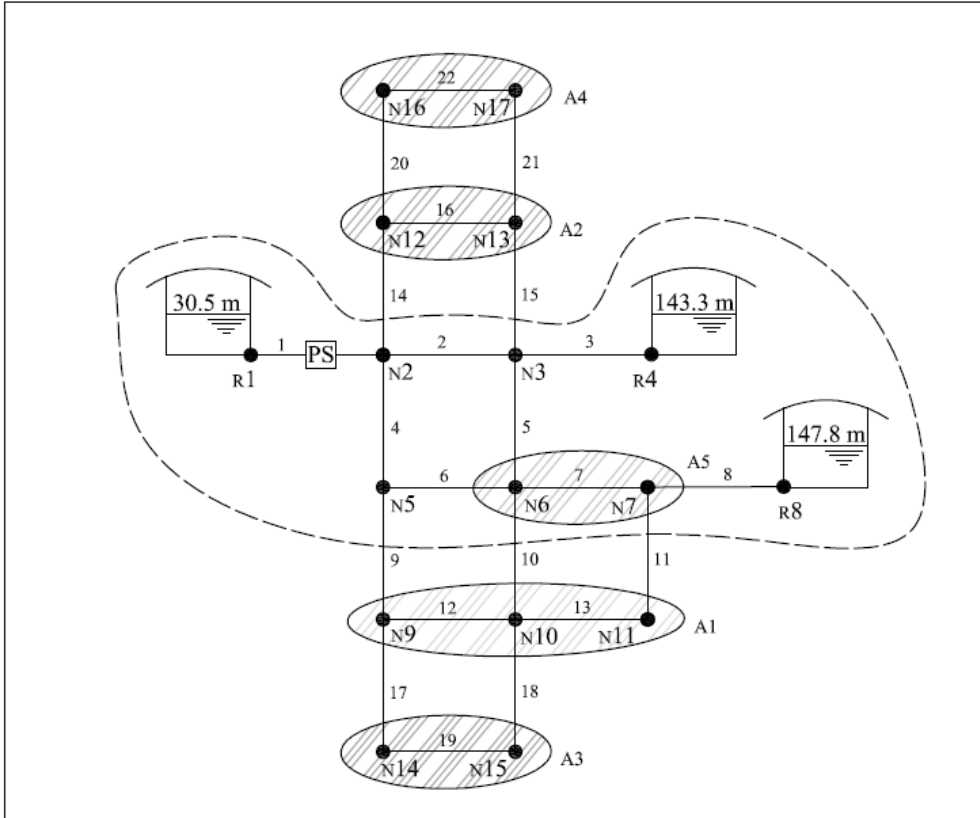
105 The new ROs approach presented in this work deals with future uncertainties
106 and with two conflicting objectives, over the whole planning horizon. Decision planning
107 based on trying to delay some decisions for the future, enables current investment to be
108 reduced. This delay also incurs some costs because the initial solution has to be flexible
109 enough to accommodate all the future conditions, and such flexibility comes at a price.

110 The remainder of this paper is organized as follows: in the next section the ROs
111 framework and the case study are set out. This is followed by a multi-objective decision
112 model based on an ROs approach, and then the results are presented. Finally, the
113 conclusions are set out.

114 **2 Real options framework and case study**

115 A real options approach makes it possible to consider different adaptations over the
116 lifetime horizon, according to urban growth. Areas can become depopulated or
117 urbanized. These modifications have impacts on the hydraulic behavior of the networks
118 and should be taken into account. In this section a case study demonstrating how the
119 multi-objective model considering ROs can be employed is presented. Figure 1
120 represents a water distribution network inspired on the work of Walski *et al.* (1990). In
121 the original case study the layout of the network is only the part represented inside the

122 dashed line. However, in this case study the possibility to expand the network for four
 123 different areas A1, A2, A3 and A4 it is considered. Furthermore an area A5 where it is
 124 possible to have a depopulated area is taken into account.



125
 126 **Figure 1:** Water distribution network inspired from Walski *et al.* (1990)

127 The network is supplied by three fixed-level reservoirs and there is a pumping
 128 station placed at link 1 to transmit energy to the flow from reservoir R1. The
 129 characteristics of the nodes at demand conditions (1) and (2) are presented in Table 1.
 130 This work considers two kinds of minimum pressure: the desired pressure and the
 131 admissible pressure of reference. The lower limit of pressures (admissible pressures) is
 132 assumed to be high enough to permit that the demand can be totally satisfied. Pressure
 133 deficits for which the demand cannot be totally satisfied (Wagner et al. 1988) are not
 134 considered here. The two different pressure levels are included to analyse the tradeoff
 135 between costs and service levels measured in terms of minimum nodal pressures that are
 136 desired and pressures that are effectively provided.

137 The efficiency of the pump is considered to be constant and equal to 75%, as a
 138 simplification of the problem and the daily consumption is 20 hours at demand
 139 condition (1) with the other 4 hours at demand condition (2). The energy costs are
 140 0.075\$/KWh and should be evaluated for a 60-year period using a discount rate of 4%
 141 year. The discount rate is just used to assess the cost in different time interval of the
 142 planning horizon. This rate was fixed based on the work of Wu *et al.* (2010).

143 **Table 1:** Characteristics of the nodes

Node	Areas	Ground elevation (m)	Nodal consumption (l/s)		Minimum desirable pressure (m)		Minimum admissible pressure (m)	
			(1)	(2)	(1)	(2)	(1)	(2)
1		36.48	Reservoir at the level of 35.48 m					
2		30.48	0	0	28.132	17.583	21.099	10.550
3		106.68	31.545	47.318	28.132	17.583	21.099	10.550
4		117.35	Reservoir at the level of 151.73 m					
5		106.68	31.545	47.318	28.132	17.583	21.099	10.550
6	A5	106.68	126.180	189.270	28.132	17.583	21.099	10.550
7	A5	106.68	63.090	94.635	28.132	17.583	21.099	10.550
8		121.92	Reservoir at the level of 156.30 m					
9	A1	106.68	31.545	47.318	28.132	17.583	21.099	10.550
10	A1	106.68	31.545	47.318	28.132	17.583	21.099	10.550
11	A1	106.68	31.545	47.318	28.132	17.583	21.099	10.550
12	A2	106.68	31.545	47.318	28.132	17.583	21.099	10.550
13	A2	106.68	31.545	47.318	28.132	17.583	21.099	10.550
14	A3	106.68	31.545	47.318	28.132	17.583	21.099	10.550
15	A3	106.68	31.545	47.318	28.132	17.583	21.099	10.550
16	A4	106.68	31.545	47.318	28.132	17.583	21.099	10.550
17	A4	106.68	31.545	47.318	28.132	17.583	21.099	10.550

144

145 This is a new network that considers the 8 different commercial diameters
 146 available for the pipe design presented in Table 2. The installation of parallel pipes
 147 during the planning horizon is not considered in this study. Carbon emissions are
 148 computed assuming a value of 0.637 KgCO₂ per each KWh of energy produced. This is
 149 a mean value of the carbon emissions of the electricity generation sector between 2005
 150 and 2010 in Portugal (ERSE 2012). The characteristics of the pipes are given in Table 3.

151 **Table 2:** Diameter, unit cost, carbon emissions and Hazen-Williams coefficients

Diameters (mm)	Unit cost (\$/m)	Carbon emissions (TonCO ₂ /m)	Hazen-Williams coefficients
152.4	49.541	0.48	100
203.2	63.32	0.59	100
254	94.816	0.71	100
304.8	132.874	0.81	100
355.6	170.932	0.87	100
406.4	194.882	0.96	100
457.2	225.066	1.05	100
508	262.795	1.14	100

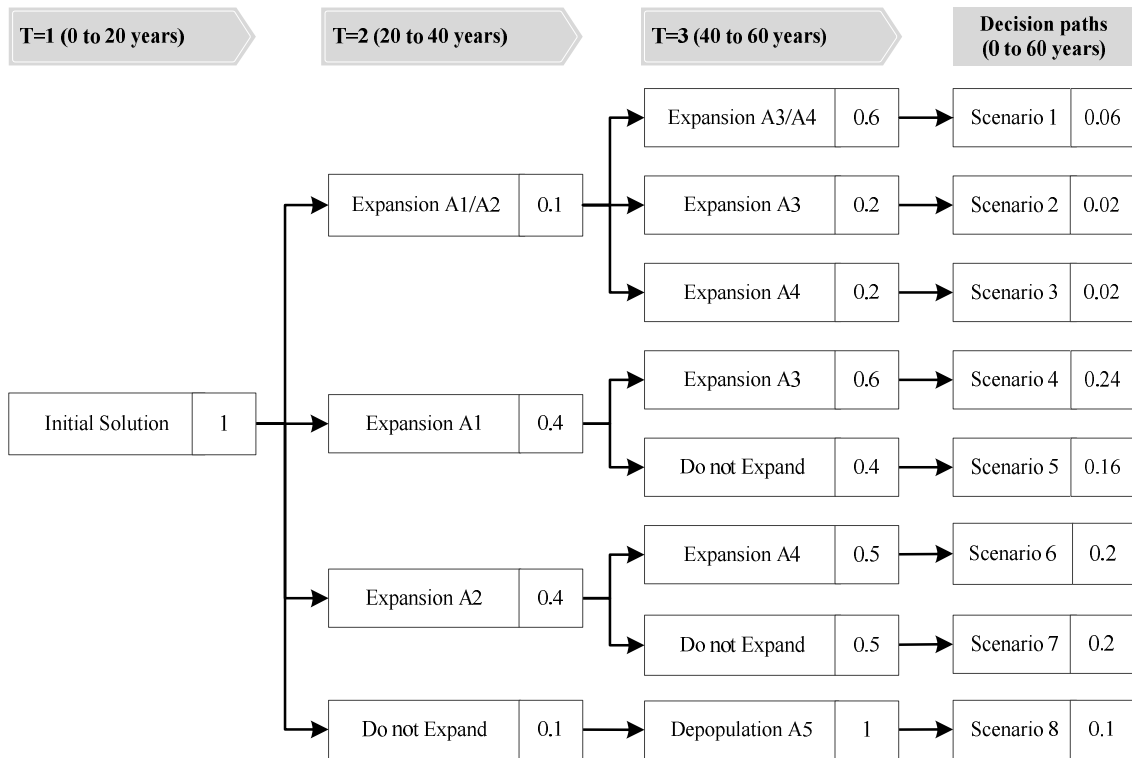
152

153 **Table 3:** Characteristics of the pipes

Pipe	Initial node	Final node	Length (m)	Area
1	1	2	Pump	
2	2	3	3218.688	
3	3	4	3218.688	
4	2	5	1609.344	
5	3	6	1609.344	
6	5	6	3218.688	
7	6	7	3218.688	
8	7	8	1609.344	
9	5	9	1609.344	A1
10	6	10	1609.344	A1
11	7	11	1609.344	A1
12	9	10	3218.688	A1
13	10	11	3218.688	A1
14	2	12	1609.344	A2
15	3	13	1609.344	A2
16	12	13	3218.688	A2
17	9	14	1609.344	A3
18	10	15	1609.344	A3
19	14	15	3218.688	A3
20	12	16	1609.344	A4
21	13	17	1609.344	A4
22	16	17	3218.688	A4

154

155 A planning horizon of 60 years is assumed for this case study, which was
 156 subdivided into 3 stages of 20 years. The decision tree contemplates 8 possible
 157 scenarios where different conditions can occur in future time intervals. The different
 158 decision paths that can be taken are schematized through the tree shown in Fig. 2.



159
 160
 161

Figure 2: Decision tree for the planning horizon and probabilities of occurrence

162 Each decision path has different probabilities. For this case study the
 163 probabilities considered for the different decision nodes are shown in the square boxes
 164 of Fig. 2. For real case studies, these probabilities have to be defined by decision
 165 makers using appropriate methods and knowledge. The values shown in the last
 166 branches of the decision tree are the probabilities of the scenarios and are calculated by
 167 multiplying the probabilities of all nodes on the path of that scenario. For the first
 168 period T=1 an initial design for the network is defined. For T=2, four different
 169 situations can occur, expansion to A1 and A2, expansion to A1, expansion to A2 and no
 170 expansion. In the last period T=3, new expansion areas are possible, A3 and A4,

171 expansion to A3, expansion to A4 and no expansion. It is also possible to have a
172 depopulated area A5 where the consumption could decrease by 30%. These scenarios,
173 included in the decision tree of Fig. 2, are deemed the most probable future conditions
174 for the case study. ROs permits an adaptive planning strategy and if the predicted future
175 conditions turn out to be wrong, the model could be rerun for more realistic scenarios.

176 This paper deals with a small water network example. In real-world large
177 networks with many pipes and with many possible plans for upgrades, the decision tree
178 can become very complex. However, the methodology presented here does allow
179 numerous scenarios to be defined, and there is no restriction on the number of
180 possibilities. However, the aim is to keep the number of options relatively small by
181 taking into account the most probable future scenarios for the water network. In that
182 case, the decision trees are easy to understand and can be easily handled by decision
183 makers and the methodology.

184 Finally a cost must be assigned to the carbon emissions. A carbon cost of 5\$ for
185 each ton of carbon emitted is assumed here. This cost is defined according to European
186 Energy Exchange 2013-2020 data.

187 **3 Optimization model**

188 This work presents a multi-objective model with two conflicting objectives. One of the
189 objectives consists in minimizing the costs of construction and operations of the
190 network. These systems are responsible for important carbon emissions during
191 construction but mostly during the operation phase. Therefore, the carbon emissions are
192 also computed to try to achieve an environmental friendly design for the water
193 distribution system. The other objective of the model is used to determine a solution

194 taking into account the level of service. As it was stated, the model considers two kinds
 195 of minimum pressures, the minimum desirable pressures and the minimum admissible
 196 pressures. If nodal pressure remains between these two limits, the pressure violations
 197 are summed for all nodes. However the model considers that the network has to obey
 198 the desirable pressure constraints for the first 20 years. In the subsequent time intervals,
 199 pressures can decrease up to admissible pressures, according to the probability of
 200 occurrence of the decision paths.

201 The decision model aims to minimize two objectives. The first one is given by
 202 Eq. 1.

$$OF1 = \text{Min} (Ci + Cf) \quad (1)$$

203 Where:

204 Ci - cost of the initial solution to be implemented for the first period in
 205 year zero (\$);

206 Cf - future costs (\$).

207
 208 The objective function $OF1$ of Eq. 1 is written so that the solution for the first
 209 period, $T=1$, can be determined while taking into account the different decision paths of
 210 the planning horizon. The objective function seeks to minimize both the initial cost and
 211 the probable future cost of the system. The term Ci computes the cost of the network for
 212 the first period $T=1$ of planning and is given by Eq. 2.

$$Ci = \left(\sum_{i=1}^{NPI} (C_{pipe_{i,1}} + CCE_{pipe_{i,1}}) + \sum_{j=1}^{NPU} (C_{ps_{j,1}}) + \sum_{d=1}^{NDC} (C_{e_{d,1}} + CCE_{e_{d,1}}) \right) \quad (2)$$

214
 215 Where:

216 NPI - number of pipes in the network;

217 $C_{pipe_{i,l}}$ - cost of pipe i in period $T=l$;
 218 $CCE_{pipe_{i,l}}$ - cost of the carbon emissions of pipe i in period $T=l$;
 219 NPU - number of pumps in the network;
 220 $C_{ps_{j,l}}$ - pumping station costs of pump j in the period $T=l$;
 221 NDC - number of demand conditions considered for the design;
 222 $Ce_{d,l}$ - present value cost of energy in demand condition d in period $T=l$;
 223 $CCEe_{d,l}$ - present value cost carbon emissions by energy in demand
 224 condition d in period $T=l$.

225 The initial cost is given by the sum of the cost of pipes, the cost of pumps and
 226 the present value of energy cost. The carbon emissions' cost of pipes and energy are
 227 also included. The carbon emissions related to other network elements as pumps are not
 228 considered, since they are neglected compared with pipe construction and energy. The
 229 other term of the objective function OFI represents the future cost of all the scenarios
 230 (Eq. 3), weighted by the corresponding probability of each scenario.

231

$$Cf = \sum_{s=1}^{NS} \sum_{t=2}^{NTI} \left(C_{future_{t,s}} \cdot \prod_{nt=2}^t prob_{nt,s} \right) \quad (3)$$

232

Where:

233

NS - number of scenarios;

234

NTI - number of periods into which the planning horizon is subdivided;

235

$C_{future_{t,s}}$ - cost of future designs in scenario s for period t ;

236

$Prob_{nt,s}$ - probability of scenario s in period nt .

237

The future scenarios' costs are arrived at by summing all possible future costs,

238

starting from $T=2$. These costs are computed by multiplying the cost of each decision

239

option by the probability of taking that decision path. A mean is obtained for the future

240 possible costs for the network. The term $C_{future_{t,s}}$ is computed in Eq. 4, for all periods
 241 beginning in $T=2$ (the costs for the first period are already calculated in the *Cinitial*
 242 term).

$$C_{future_{t,s}} = \left(\sum_{i=1}^{NPI} (C_{pipe_{i,t,s}}) + \sum_{j=1}^{NPU} (C_{ps_{j,t,s}}) + \sum_{d=1}^{NDC} (C_{e_{d,t,s}}) \right) \cdot \frac{1}{(1+IR)^{Y_t}} + \left(\sum_{i=1}^{NPI} (CCE_{pipe_{i,t,s}}) + \sum_{d=1}^{NDC} (CCE_{e_{d,t,s}}) \right) \quad (4)$$

243 Where:

- 244 NPI - number of pipes in the network;
 245 $C_{pipe_{i,t}}$ - cost of pipe i installed in period t in scenario s ;
 246 NPU - number of pumps in the network;
 247 $C_{ps_{j,t,s}}$ - pumping station costs of pump j installed in period t in scenario s ;
 248 NDC - number of demand conditions considered for design;
 249 $C_{e_{d,t,s}}$ – present value cost of energy (actualized for the first year of the
 250 time interval t) in demand condition d for period t in scenario s ;
 251 $CCE_{pipe_{i,t,s}}$ - cost of the carbon emissions of pipe i installed in period t in
 252 scenario s ;
 253 $CCE_{e_{d,t,s}}$ – present value cost carbon emissions by energy in demand
 254 condition d for period t in scenario s ;
 255 IR - annual interest rate for updating cost;
 256 Y_t - year when costs will be incurred for period t .

257 The first term of Eq. 4 computes the cost of pipes to be installed for different
 258 decision paths plus the costs to install pumps every 20 years plus the cost of energy. The
 259 current value of these cost are then determined. To compute the current value of the
 260 costs of energy, it is necessary to sum and discount the costs during the number of years
 261 of each the time interval. Thereafter, it is required to update these costs by Y_t years to

262 year zero of the planning horizon. The carbon emission costs associated with pipe
 263 installation and with energy consumption are included in the second term.

264 The sum of the initial costs with future costs is intended to represent the full
 265 planning horizon of the network, considering future uncertainty. The model aims to
 266 determine the decision variables not only for the first period but also for all the future
 267 decisions that have to be taken according to certain possible decision paths. The values
 268 of the decision variables that are achieved for the first period are effectively the ones
 269 that are needed to be adopted now.

270 The second objective function is given in (5). The aim of this expression is to
 271 minimize the total pressure violations for the different future scenarios.

$$OF2 = Min (TPV) \quad (5)$$

272 Where:
 273 TPV - total pressure violations (m).

274 The multi-objective model determines different solutions for different levels of
 275 pressure violations. The total pressure violations are computed according to Eq. 6:

$$TPV = \sum_{s=1}^{NS} \sum_{t=2}^{NTI} \sum_{d=1}^{NDC} \sum_{n=1}^{NN} Max \left\{ 0; (Pdes_{min,n,d} - P_{n,d,t,s}) \right\} \quad (6)$$

276 Where:
 277 NN - number of nodes;
 278 $Pdes_{min,n,d}$ - minimum desirable pressure at node n for demand condition
 279 d ;
 280 $P_{n,d,t,s}$ - pressure at node n at demand condition d for time interval t and in
 281 scenario s .

282 Eq. 6 computes the sum of pressure violations for each scenario, each time
 283 interval (starting from $T=2$), each demand condition and each network node. This sum

284 of pressure violations can be used as a measure of the network performance during the
 285 entire planning horizon.

286 Table 1 presents the desirable and admissible minimum pressures for each node.
 287 However these admissible pressures are a threshold limit to compute the lowest value
 288 that the nodal pressures can reach according to the probability of scenarios. The
 289 constraint presented in expression (7) aims to obtain higher values, and thus less
 290 pressure violations, for scenarios with high probabilities of occurrence. In the first time
 291 interval, a decision node with probability equal to 1 is only considered. If in expression
 292 (7) the probability is set to 1, the minimum pressure become equal to the desired
 293 pressure. Thus, for the first time interval the pressures have to be higher or equal to
 294 desirable pressures and no violations are permitted in the first time stage.

$$P_{n,d,t,s} \geq \left\{ \prod_{nt=2}^t \text{prob}_{nt,s} (Pdes_{\min,n,d} - Padm_{\min,n,d}) + Padm_{\min,n,d} \right\} \quad (7)$$

$\forall n \in NN; \forall d \in NDC; \forall nt \in NTI; \forall s \in NS$

295 Where:

296 $Padm_{\min,n,d}$ - minimum admissible pressure at node n for demand
 297 condition d .

298 Expression (7) is just one of the constraints of the model. The model also
 299 includes other constraints: Eq. (8) to verify the nodal continuity equations; Eq. (9) to
 300 compute the head loss of the pipes; Eq. (10) to guarantee a minimum diameter for the
 301 pipes; Eq. (11) so the candidate discrete diameter for each pipe is based on a set of
 302 commercial diameters; and Eq. (12) to ensure the assignment of only one commercial
 303 diameter for each pipe. The decision variables of this optimization problem described
 304 by Eq. (1 to 12) are the commercial pipe diameter assigned to each pipe of the network.

$$305 \quad \sum_{i=1}^{NPI} I_{n,i} Q_{i,d,t,s} = QC_{n,s} \quad \forall n \in NN; \forall d \in NDC; \forall t \in NTI; \forall s \in NS \quad (8)$$

$$306 \quad \Delta H_{i,d,t,s} = K_i Q_{i,d,t,s}^\alpha \quad \forall n \in NN; \forall d \in NDC; \forall t \in NTI; \forall s \in NS \quad (9)$$

$$307 \quad D_i \geq D \min_i \quad \forall i \in NPI \quad (10)$$

$$308 \quad D_i = \sum_{d=1}^{ND} YD_{d,i} \cdot Dcom_{d,i} \quad \forall i \in NPI \quad (11)$$

$$309 \quad \sum_{d=1}^{ND} YD_{d,i} = 1 \quad \forall i \in NPI \quad (12)$$

310 Where:

311 $I_{n,i}$ - incidence matrix of the network;

312 $Q_{i,d,t,s}$ - flow on the pipe i in demand condition d for period t and scenario
313 s (m^3/s);

314 $QC_{n,d,t,s}$ - consumption in node n in demand condition d for period t and
315 scenario s (m^3/s);

316 NN - number of nodes;

317 $\Delta H_{i,s}$ - head loss in pipe i in demand condition d for period t and
318 scenario s ;

319 K_i, α - coefficients that depends of the physic characteristics of the pipe i ;

320 D_i - diameter of pipe i ;

321 $D \min_i$ - minimum diameter for the pipe i ;

322 $YD_{d,i}$ - binary variable to represent the use of the diameter d in pipe i ;

323 $Dcom_{d,i}$ - commercial diameter d assigned to pipe i ;

324 ND - number of commercial diameters.

325 4 Optimization tool

326 A new method has been developed to solve the multi-objective model. This work
327 presents a multi-objective simulated annealing algorithm inspired by the work of
328 Bandyopadhyay *et al.* (2008). In these problems the objective is to search for a group of
329 optimal solutions that are normally named “optimal Pareto front”, introduced by Pareto
330 (1896). These solutions are characterized by the fact that it is not possible to enhance
331 one objective without worsening the other.

332 The original simulated annealing method for single-objective problems proposed
333 by Kirkpatrick *et al.* (1983) needs some changes before multi-objective optimization
334 problems can be solved. A fundamental difference is the use of a dominance concept to
335 guide the exploration of neighborhoods during the search process. The concept of
336 dominance is generally used to compare two solutions s_i and s_j . If s_i is not worse for
337 all the objectives than s_j and only better for at least one objective, it is said that s_i
338 dominates s_j . Also, a solution s_{opt} is said to be non-dominated if no other feasible
339 solution found so far dominates it. The set of non-dominated solutions s_{opt} is known as a
340 Pareto optimal front.

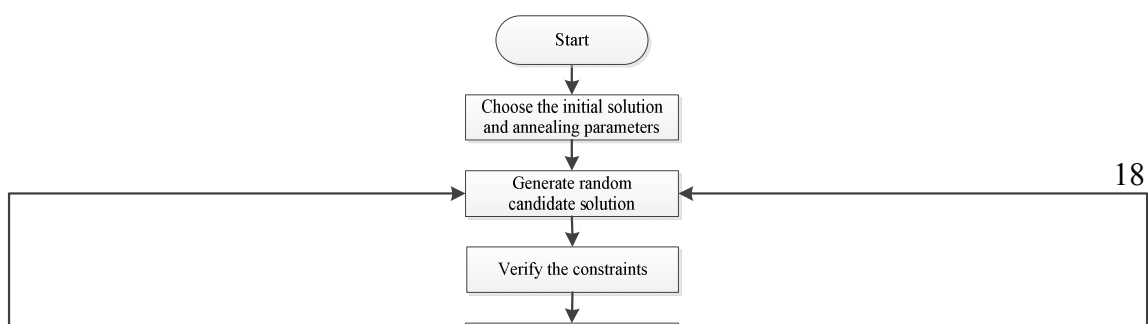
341 This method makes use of an archive where the non-dominated solutions seen so
342 far are stored. The structure of the proposed optimization tool is presented in Fig 3.

343

344

345

346



347

348

349

350

351

352

353

354

355

356

357

358

359

360

361

362 **Figure 3:** Multi-objective simulated annealing flow chart

363

364 Some parts of the algorithm are similar to the single-objective simulated
 365 annealing tool: the initial solution, the annealing parameters, the building method of the
 366 neighborhoods, the cooling process and the stop criteria that are given in the work of
 367 Cunha & Sousa (2001) are also used in this method. But some important differences are
 368 highlighted below.

369 After the generation of a candidate solution and verification of the constraints of
 370 the model we must check the domination status. This is the key difference between the
 371 single-objective and multi-objective tools based on simulated annealing. In the single-
 372 objective method the candidate solution is accepted according to the Metropolis
 373 criterion that compares the current solution with the candidate solution. However, in
 374 this multi-objective method the candidate solution is compared both with the current
 375 solution and with the solutions saved in the archive.

376 The dominance between two solutions is computed by Eq. 13:

$$\Delta dom_{a,b} = \prod_{i=1, OF_i(a) \neq OF_i(b)}^N |OF_i(a) - OF_i(b)| \quad (13)$$

377

378 Where:

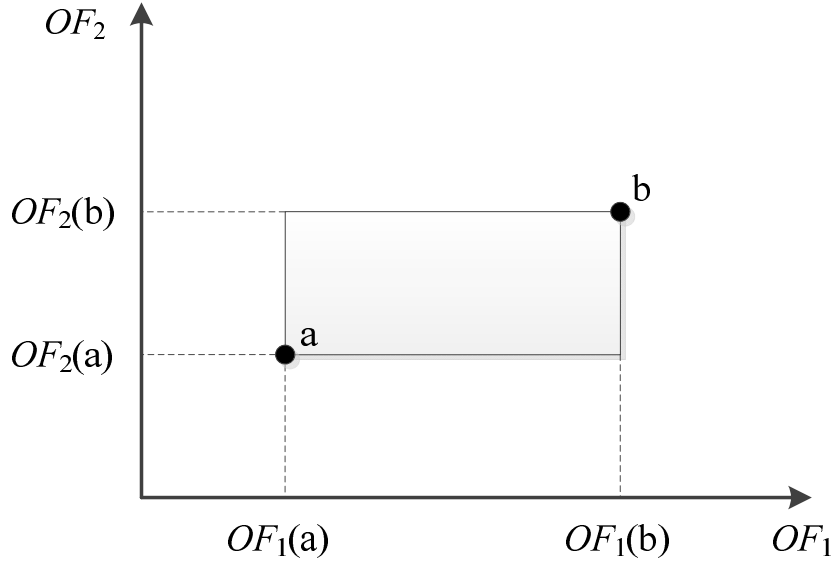
379 $\Delta dom_{a,b}$ – dominance a to b ;

380 N – total number of objectives;

381 $OF_i(a)$ – value of objective function i for solution a ;

382 $OF_i(b)$ – value of objective function i for solution b .

383 The dominance between two solutions is computed by multiplying the change in
 384 the values of the N objectives, if this difference is other than zero. The domination
 385 concept is explained in Fig. 4 for the example of two objective functions.



386

387 **Figure 4:** Domination between solutions a and b , adapted from Bandyopadhyay *et al.*

388 (2008)

389 The amount of domination is represented in Fig. 4 by the area of the rectangle
 390 between solutions a and b and is used by the multi-objective simulated annealing to
 391 compute the acceptance probability.

392 Three different conditions can occur when checking the domination status:
 393 current solution dominates candidate solution; candidate and current solutions are non-
 394 dominated and candidate solution dominates current solution. According to the
 395 domination status, it can also be necessary to compute the dominance of the candidate
 396 solution in relation to the solution in the archive. According to the situation, the solution
 397 can be accepted directly and become the new current solution. But, if the candidate
 398 solution is dominated by current solution or by the archive, a metropolis criterion is
 399 used to compute the acceptance probability for three distinct cases of dominance, as
 400 presented in Fig. 3. For case 1, the dominance is computed by Eq. 14:

$$\Delta dom_{mean} = \frac{\left(\sum_{i=1}^p \Delta dom_{i,cand} \right) + \Delta dom_{curr,cand}}{p+1} \quad (14)$$

401

402

Where:

403

Δdom_{mean} – mean dominance relative to the candidate solution;

404

$\Delta dom_{i,cand}$ – dominance of the archive relative to the candidate solution;

405

$\Delta dom_{curr,cand}$ – dominance of the current solution relative to the candidate solution;

406

407

p – total number of solutions in the archive that dominate the candidate

408

solution.

409

Eq. 9 considers not only the dominance of the current solution in relation to the

410

candidate solution, but also the sum of dominance of all the solutions in the archive that

411

dominate the candidate solution. This sum is divided by the number of solutions in the

412

archive that dominate the candidate solution, plus one, to take into account the

413

dominance of the current solution relative to the candidate solution. For case 2, the

414

current and candidate solutions are non-dominated and the mean dominance is

415

computed by Eq. 15:

$$\Delta dom_{mean} = \frac{\left(\sum_{i=1}^p \Delta dom_{i,cand} \right)}{p} \quad (15)$$

416

417

This expression is analogous to case 1, except that now the dominance between

418

the current and candidate solutions is not taken into account. Lastly, for case 3, the

419

candidate solution dominates the current solution. But if the archive dominates the

420

candidate solution a minimum dominance is computed through Eq. 16, deemed equal to

421

the minimum value of dominance between the solutions of the archive that dominate the

422

candidate solution.

$$\Delta dom_{min} = \text{Min}(\Delta dom_{i,cand}, i = 1, \dots, p) \quad (16)$$

423 Where:

424 Δdom_{min} – minimum dominance relative to candidate solution.

425

426 After calculating the dominance in these three different cases the Metropolis
427 criterion is used to compute the acceptance probability of the candidate solution. For
428 cases 1 and 2 the acceptance probability is computed by Eq. 17, and for case 3 the
429 acceptance probability is computed by Eq. 18:

430

$$P_{acp} = \exp\left(\frac{-\Delta dom_{mean}}{T}\right) \quad (17)$$

$$P_{acp} = \exp\left(\frac{-\Delta dom_{min}}{T}\right) \quad (18)$$

431

432 For cases 1 and 2, if the Metropolis criterion is met the current solution becomes
433 the candidate solution. For case 3, if the Metropolis criterion is met the current solution
434 becomes equal to the solution of the archive with the minimum dominance relative to
435 the candidate solution. These movements are also called uphill moves because they are
436 contrary to the direction to the minima can be accepted according to the computed
437 probabilities. This method is thus able to explore, in theory, the full solution space and
438 the solutions achieved, regardless of the starting point of the algorithm.

439 According to the structure of the algorithm of Fig. 3, the multi-objective process
440 is repeated for a number of iterations at each temperature. The temperature is reduced
441 until the stop criteria are attained and the process stops.

442 The archive contains the non-dominated solutions found so far. The size of the
443 archive is given by two limits, a lower limit LL and an upper limit SL . During the search

444 process, solutions are stored in the archive until it is completed with *SL* solutions. Then
445 a clustering technique is used to lower the number of solutions stored to the lower limit
446 *LL*. The clustering technique is based on the work of Hartigan and Wong (1979). This
447 tool aims to find a small number of *LL* solutions that represents the group of *SL*
448 solutions. The values are *LL*=10 and *SL*=30 and are defined according to the number of
449 final of Pareto front solutions that we wish to obtain.

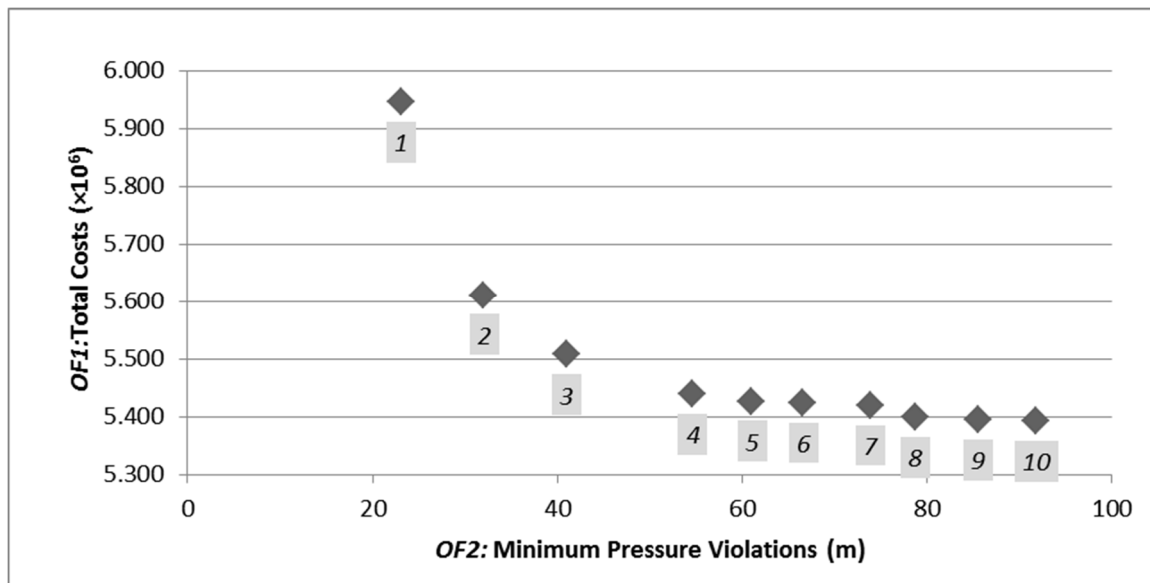
450 This optimization method was linked to the EPANET hydraulic simulator
451 (Rossman, 2000) to verify the hydraulic constraints of the multi-objective model.
452 Although this is a demand driven hydraulic simulator, the methodology included in this
453 paper could be easily adapted for a pressure driven hydraulic simulator to include issues
454 related to network deterioration and leakages.

455 In this work a simple water network it is used to illustrate the approach. For
456 large size networks the computation demand increases due to the size of the network,
457 which has impacts on how quickly the RO problem can be solved. For large networks, if
458 the computation time increases too much, some strategies can be used to overcome this
459 problem: considering just the more important parts or by dividing the network in
460 subzones, such as district metered areas (DMAs) or using parallel computing.

461 **5 Results**

462 Figure 5 provides some results obtained by solving the multi-objective model given by
463 the objective functions and constraints (Eq. 1 to 12). The model determines the Pareto
464 front consisting of 10 different solutions. The total cost represents not only the
465 investment and operation costs but also the carbon emission costs of the network
466 lifecycle. The minimum pressure violations are arrived at by summing all the violation

467 values for each node and considering the different conditions that the network can cope
468 with.



469

470 **Figure 5:** Pareto front of objectives *OF1* and *OF2*

471

472

473

474

475

476

477

478

479

480

481

482

483

484

The Pareto front that can be traced through the points represented in Fig. 5 gives an idea about how the cost decreases when pressure violations are permitted. Fig.5 provides the Pareto front identified by the optimization tool. This figure represents 10 distinct solutions. The number of solutions is given a by the lower limit of the archive *LL*. This limit is defined according to the number of final solutions required. If it is necessary to identify a high number of solutions, with the objective to obtain an extended Pareto Front in terms of cost (Higher costs than 5.784×10^6) or lower pressure violations (lower than 23 m) the number of final solutions has to increase. However, the computational effort will also increase. These 10 solutions were achieved in approximately 2.5×10^5 evaluations. Details of the cost of pipes, pumps and energy (PPE), carbon emission costs, total costs and total pressure violations for each solution of the Pareto front are given in Table. 4.

485 **Table 4:** Pareto front solutions

Solution	1	2	3	4	5	6	7	8	9	10
PPE cost \$($\times 10^6$)	5.784	5.461	5.358	5.291	5.279	5.276	5.273	5.253	5.248	5.246
Carbon cost \$($\times 10^6$)	0.161	0.150	0.149	0.148	0.148	0.148	0.147	0.147	0.146	0.146
Total cost \$($\times 10^6$)	5.945	5.611	5.507	5.439	5.427	5.424	5.420	5.399	5.395	5.392
Pressure Viol. (m)	23	32	41	55	61	67	74	79	85	92

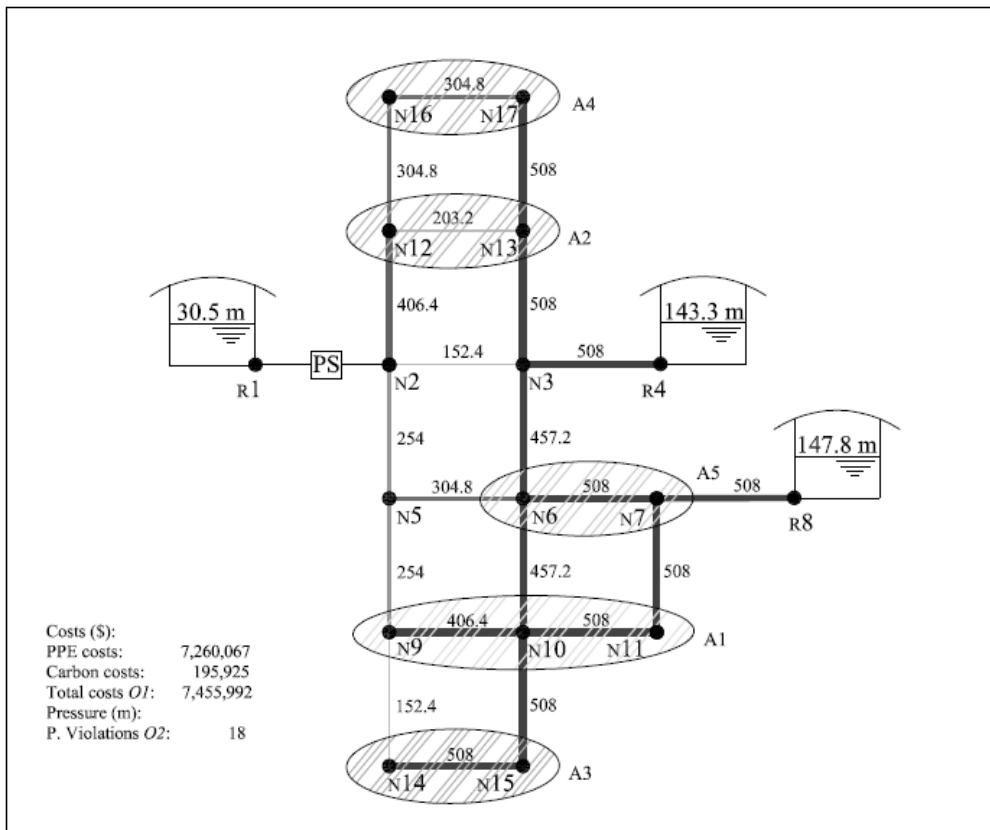
486

487 Table 4 also shows that the total cost falls if high pressure violations are
 488 allowed. A higher level of service requires an increase in the network capacity to meet
 489 the minimum desirable pressures of the network. We can also see that for solutions 10
 490 to 4 a small increment in the total cost makes it possible to define solutions with
 491 significant falls in the total minimum pressure violations. Thus, it is possible to improve
 492 the level of service of the network within this range of solutions for a low expenditure.

493 The carbon emission cost falls as the PPE cost decreases, as indicated in Table 4.
 494 The carbon emission varies for different solutions on the Pareto front between a
 495 minimum of \$146,227 for solution 10 and a maximum of \$161,019 for solution 1. In
 496 fact, the variation in carbon costs for these 10 solutions is small and thus the impact on
 497 the optimization process is low. This value is nonetheless included in the model to
 498 quantify the carbon emissions involved in construction and operation of water networks.

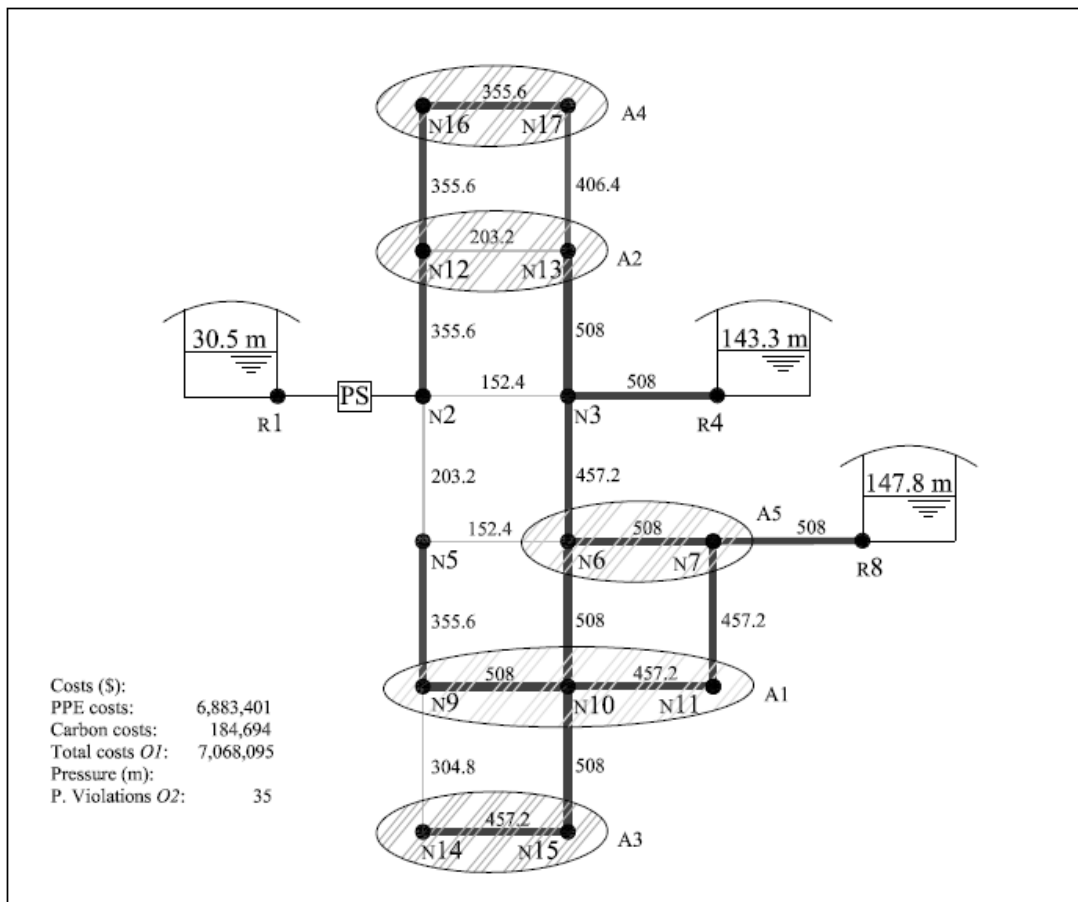
499 In order to explain how solutions are defined, the extremities of the Pareto front
 500 (solution 1 and solution 10) will be detailed next, just for the first scenario.. Fig 6 shows
 501 the total cost of the solution 1, for scenario 1 and for the 60-year planning horizon, is
 502 \$7,455,992 and is composed of PPE costs of \$7,260,067 and carbon emission costs of
 503 \$195,925, associated with the design and operation of the network. The total cost of
 504 solution 10 (Fig. 7) for the same scenario and for the 60-year planning horizon, is

505 \$7,068,095 and consists of PPE costs of \$6,883,401 and carbon emission costs of
 506 \$184,694. In this scenario all the areas are expanded, thus the total consumption in the
 507 network increases. This is the most demanding case considered in the decision tree and
 508 has a 6% probability of occurrence. The diameters are given in millimeters and the
 509 expansion areas are indicated by traced ellipses aggregating the new consumption
 510 nodes.



511

512 **Figure 6:** Design for solution 1 and considering scenario 1 in the last time interval



513

514 **Figure 7:** Design for solution 10 and considering scenario 1 for the last time interval

515 In terms of violations, solution 1, for scenario 1, has 18m and solution 10, for
 516 scenario 1, has 35m total minimum pressure violations. Differences between solutions
 517 indicate that a cost increment of 6% is needed for scenario 1 to lower the total minimum
 518 pressure violations by 17m. Also, the carbon emission costs increase 6% if a network
 519 with low pressure violations is required.

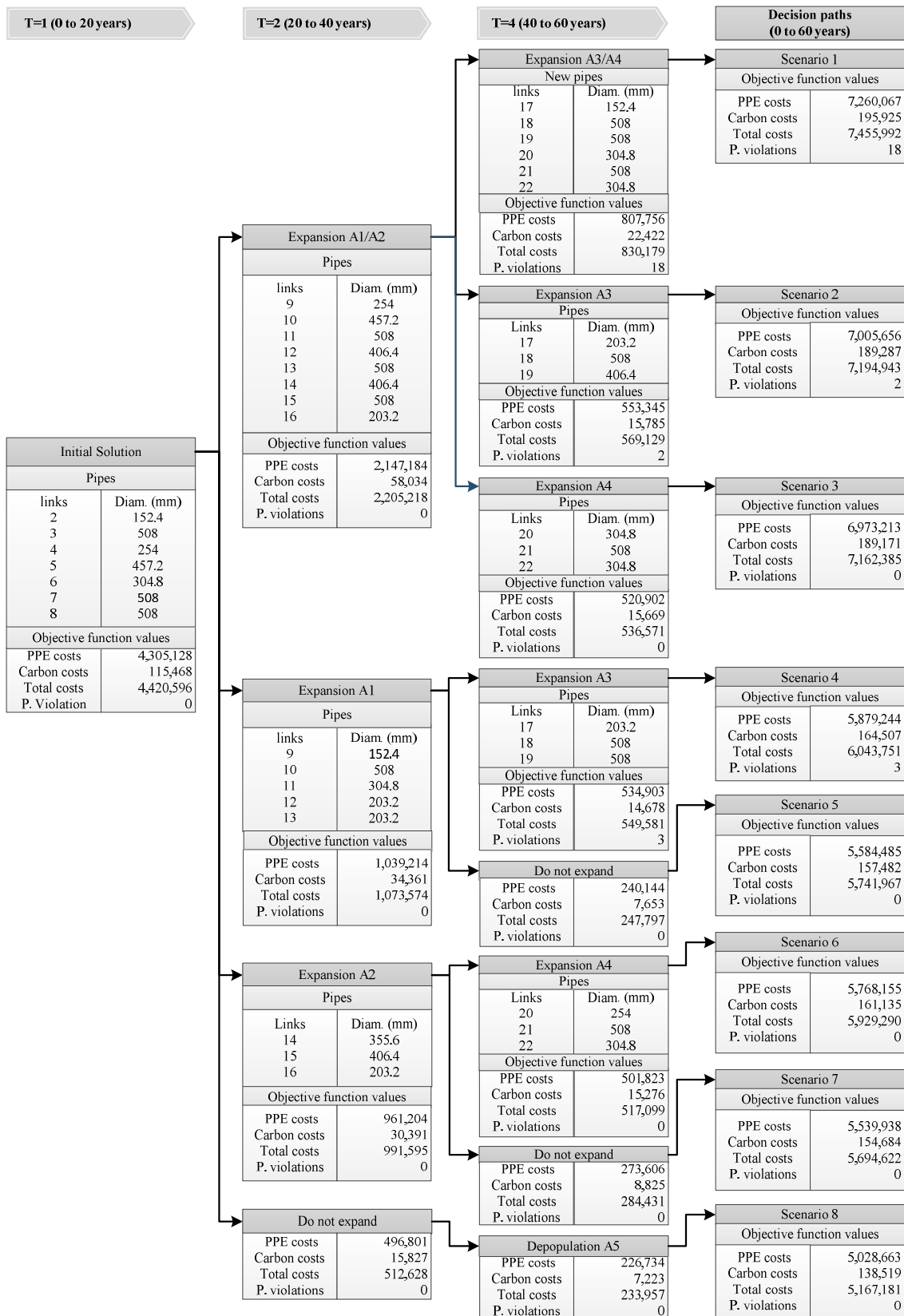
520 The optimization model aims to simultaneously minimize the installation,
 521 operation and carbon emission costs of the first objective function *OF1*. But it also aims
 522 to minimize the pressure violations given by objective function *OF2*. The designs
 523 represented by Figs 6 and 7 can be used as solutions for the case study described in this
 524 work if scenario 1 occurs. However, other solutions given by the multi-objective model
 525 can be chosen, according to the preferences of decision makers. All the possible

526 decision paths of solution 1 of the Pareto front in Fig. 5 determined by the multi-
527 objective tool, are shown in greater detail in Fig. 8.

528 Decisions have to be made for each time interval of the decision tree. Fig. 8
529 presents, for each node, a table with the results of design solution 1 of the Pareto front,
530 beginning with the diameters of pipes (in millimeters) required in the network. Then the
531 costs are shown, divided into PPE costs, carbon costs, total cost and minimum pressure
532 violations. Finally, the last branches of the decision tree represent the total cost of PPE,
533 carbon emissions, total cost and total pressure violations for each scenario. These
534 figures represent, for each scenario, the total cost and pressure violations that may be
535 expected if that scenario occurs.

536 Only the first stage design decision has to be implemented now, and therefore
537 the future decisions will be made as new information comes. At the end of each phase
538 the methodology should be applied again and different scenarios from those considered
539 initially could be considered (Creaco *et al.* 2014). The ROs approach is formulated as a
540 multi-stage model whose objective is to design the network for the first time interval
541 and help decision makers to find the best system development strategy while
542 minimizing the costs.

543 The design for the network depends not only on the hydraulic conditions of the
544 present decision but on the decision paths that can be followed, too. The decisions taken
545 in prior stages have to accommodate the future possible conditions of the network. The
546 ROs approach considers different scenarios with different probabilities. By adding
547 together the initial cost and all the future weighted costs we can arrive at the present
548 value of the ROs solution in the Pareto front, which is $\$5.945 \times 10^6$. The sum of all
549 pressure violations at the nodes of the network for this solution is 23m.



553 **Figure 8:** Designs for solution 1 according to the planning horizon decision tree

554
555 The design achieved for each link has enough capacity to extend the network to
556 future new areas that may be built. Pipes 2 to 8 (see Fig. 1) are designed in the first
557 stage, but need to have enough capacity for different decision paths. However, there is a
558 tradeoff to determine the minimum cost solution involving carbon emissions and the
559 minimum pressure violations that are allowed in the planning horizon.

560 **6 conclusions**

561 An ROs approach has been described that takes future uncertainties into account and
562 deals with conflicting objectives over the whole planning horizon. A case study has
563 been detailed with some possible expansion areas defined for different future scenarios.
564 This was followed by a multi-objective decision model based on an ROs approach. The
565 model aims to minimize two objectives and cope with all the different planning horizon
566 scenarios that are considered. The objective functions and their constraints determine
567 the solutions to be implemented in the first period, $T=1$, while taking into account all
568 the possible future conditions that the network may have to cope with. ROs enable
569 initial investments to be reduced by postponing some decisions for the future.

570 The model aims to minimize two objectives. The first is given by the total cost
571 computed as the sum of the installation cost of pipes and pumps plus the energy costs
572 and the carbon cost over the lifecycle of the network. These costs are actualized to year
573 zero and weighted by the probabilities of the future scenarios. The second objective is to
574 minimize the minimum desirable pressure violations computed by summing the extent
575 of the violation for all the nodes of the network and for all the scenarios. This objective
576 can be seen as a level of service measure for the water supply system. The model is
577 solved by a multi-objective simulated annealing heuristic and the results are represented

578 as points on the Pareto front. Carbon emissions are considered in the model. These
579 environmental impacts are reduced by decreasing the size of the diameters and by
580 cutting energy consumption. But, in this case study, there is a relationship between the
581 pipe design and the energy consumed by pumps. Energy consumption can be reduced
582 by using large pipe diameters that decrease the head losses, thereby reducing the amount
583 of energy required to pump water. The optimization model has to handle this tradeoff.

584 A group of solutions is obtained by the multi-objective model. These results
585 enable decision makers to choose which solution to implement according to some
586 preferences. One of these solutions is shown in more detail by means of a decision tree,
587 including the values for the different decision variables, the total investment, the
588 operating and carbon emission costs that will be incurred, and the minimum pressure
589 violations.

590 From the results, it was concluded that the carbon emission costs do not have a
591 significant influence on the objective function value. As future trends, carbon emission
592 costs should be included explicitly in the multi-objective optimization model to express
593 the compromise between the minimization of these eco-friendly aspects and the other
594 objectives. Furthermore, energy and pipe costs are conflicting with each other and the
595 cost of energy could be viewed as another distinct objective to optimize.

596 Overall, this study suggests that the multi-objective optimization tool based on
597 ROs and considering environmental impacts can be used for solving water network
598 design and operation problems with a long-term and uncertain planning horizon. The
599 results also suggest that a multi-objective simulated annealing method can be
600 successfully applied, leading to sparse Pareto front solutions.

601 **7 Acknowledgments**

602 This work has been financed by FEDER funds through the Programa
603 Operacional Factores de Competitividade – COMPETE, and by national funds from
604 FCT –Fundação para a Ciência e Tecnologia under grant PTDC/ECM/64821/2006. The
605 participation of the first author in the study is supported by FCT – Fundação para a
606 Ciência e Tecnologia through Grant SFRH/BD/47602/2008.

607 **8 References**

- 608 Ahmadi, M., Arabi, M., Ascough, J. C., Fontane, D. G., and Engel, B. A. (2014).
609 Toward improved calibration of watershed models: Multisite multiobjective
610 measures of information. *Environmental Modelling & Software*, 59, 135–145.
- 611 Bandyopadhyay, S., Saha, S., Maulik, U., and Deb, K. (2008). A Simulated Annealing-
612 Based Multiobjective Optimization Algorithm: AMOSA. *Evolutionary*
613 *Computation, IEEE Transactions on*.
- 614 Basupi, I., and Kapelan, Z. (2013). Flexible Water Distribution System Design under
615 Future Demand Uncertainty. *Journal of Water Resources Planning and*
616 *Management*.
- 617 Creaco, E., and Franchini, M. (2012). Fast network multi-objective design algorithm
618 combined with an a posteriori procedure for reliability evaluation under various
619 operational scenarios. *Urban Water Journal*, 9(6), 385–399.
- 620 Creaco, E., Franchini, M., and Walski, T. (2014). Accounting for Phasing of
621 Construction within the Design of Water Distribution Networks. *Journal of Water*
622 *Resources Planning and Management*, 140(5), 598–606.
- 623 Cunha, M., and Sousa, J. (2001). Hydraulic Infrastructures Design Using Simulated
624 Annealing. *Journal of Infrastructure Systems*, 7(1), pp. 32–39.
- 625 Dandy, G., Roberts, A., Hewitson, C., and Chrystie, P. (2006). Sustainability Objectives
626 For The Optimization Of Water Distribution Networks. In W. D. S. A. S. 2006
627 (Ed.), *Water Distribution Systems Analysis Symposium 2006* (pp. 1–11). American
628 Society of Civil Engineers.
- 629 De Neufville, R., Scholtes, S., and Wang, T. (2006). Real Options by Spreadsheet:
630 Parking Garage Case Example. *Journal of Infrastructure Systems*, 12(2), 107–111.

- 631 Dennison, F. J., Azapagic, A., Clift, R., and Colbourne, J. S. (1999). Life cycle
632 assessment: Comparing strategic options for the mains infrastructure — Part I.
633 *Water Science and Technology*, 39(10–11), 315–319.
- 634 Di Pierro, F., Khu, S.-T., Savić, D., and Berardi, L. (2009). Efficient multi-objective
635 optimal design of water distribution networks on a budget of simulations using
636 hybrid algorithms. *Environ. Model. Softw.*, 24(2), 202–213.
- 637 ERSE. (2012). *Comércio Europeu de Licenças de Emissão de Gases com Efeito de*
638 *estufa* (p. 30).
- 639 Farmani, R., Savic, D., and Walters, G. (2004). The Simultaneous Multi-Objective
640 Optimization of Anytown Pipe Rehabilitation, Tank Sizing, Tank Siting, and Pump
641 Operation Schedules. In *Critical Transitions in Water and Environmental*
642 *Resources Management* (pp. 1–10). American Society of Civil Engineers.
- 643 Fonseca, C. M., and Fleming, P. J. (1993). Genetic Algorithms for Multiobjective
644 Optimization: Formulation Discussion and Generalization. In *Proceedings of the*
645 *5th International Conference on Genetic Algorithms* (pp. 416–423). San Francisco,
646 CA, USA: Morgan Kaufmann Publishers Inc.
- 647 Gersonius, B., Ashley, R., Pathirana, A., and Zevenbergen, C. (2010). Managing the
648 flooding system’s resiliency to climate change. *Proceedings of the Institution of*
649 *Civil Engineers Engineering Sustainability*, 163(1), 15–22.
- 650 Giuliani, M., Galelli, S., and Soncini-Sessa, R. (2014). A dimensionality reduction
651 approach for many-objective Markov Decision Processes: Application to a water
652 reservoir operation problem. *Environmental Modelling & Software*, 57, 101–114.
- 653 Haimes, Y. Y. (1998). Sustainable Operation of Threatened Infrastructures. *Journal of*
654 *Infrastructure Systems*, 4(1), 1–4.
- 655 Hakanen, J., Sahlstedt, K., and Miettinen, K. (2013). Wastewater treatment plant design
656 and operation under multiple conflicting objective functions. *Environmental*
657 *Modelling & Software*, 46, 240–249.
- 658 Hartigan, J. A., and Wong, M. A. (1979). Algorithm AS 136: A k-means clustering
659 algorithm. *Applied Statistics*, 28(1), 100–108.
- 660 Herstein, L., Filion, Y., and Hall, K. (2011). Evaluating the Environmental Impacts of
661 Water Distribution Systems by Using EIO-LCA-Based Multiobjective
662 Optimization. *Journal of Water Resources Planning and Management*, 137(2),
663 162–172.
- 664 Huang, D., Vairavamoorthy, K., and Tsegaye, S. (2010). Flexible Design of Urban
665 Water Distribution Networks. In *World Environmental and Water Resources*
666 *Congress* (pp. 4225–4236).
- 667 Kirkpatrick, S., Jr., C. D. G., and Vecchi, M. P. (1983). Optimization by simulated
668 annealing. *Science*, 220(4598), 671–680.

- 669 Marques, J. C. R.; Cunha, M. C.; Savic, D. (2014a) “Using Real Options for an Eco-
670 friendly Design of Water Distribution Systems”. *Journal of Hydroinformatics In*
671 *Press, IWA Publishing 2014* | doi:10.2166/hydro.2014.122
- 672 Marques, J. C. R.; Cunha, M. C.; Savic, D. (2014b) “Using Real Options in the Optimal
673 Design of Water Distribution Networks”. *Journal of Water Resources Planning*
674 *and Management*, n. 1274. *accepted for publication.*
- 675 Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial*
676 *Economics*, 5(2), 147–175.
- 677 Nembhard, H. B., and Aktan, M. (2010). Real options in engineering design, operations,
678 and management. *Production Planning & Control*, 21(7), 718–719.
- 679 Pareto, V. (1896). *Cours d’Economie Politique*. Gen`eve: Droz.
- 680 Prasad, T. D., Hong, S.-H., and Park, N. (2003). Reliability based design of water
681 distribution networks using multi-objective genetic algorithms. *KSCE Journal of*
682 *Civil Engineering*, 7(3), 351–361.
- 683 Rossman, L. A. (2000). Epanet 2 users manual. (U. S. E. P. Agency, Ed.)*Cincinnati US*
684 *Environmental Protection Agency National Risk Management Research*
685 *Laboratory*, 38(September), 200.
- 686 Sacks, J., Welch, W. J., Mitchell, T. J., and Wynn, H. P. (1989). Design and Analysis of
687 Computer Experiments. *Statistical Science*, 4(4), 409–423.
- 688 Savic, D. (2002). Single-objective vs. Multiobjective Optimisation for Integrated
689 Decision Support,. In *In: Integrated Assessment and Decision* (pp. 7–12).
- 690 Suttinon, P., and Nasu, S. (2010). Real Options for Increasing Value in Industrial Water
691 Infrastructure. *Water Resources Management*, 24(12), 2881–2892.
- 692 Todini, E. (2000). Looped water distribution networks design using a resilience index
693 based heuristic approach. *Urban Water*, 2(2), 115–122.
- 694 Wagner, J. M., Shamir, U., and Marks, D. H. (1988). Water Distribution Reliability:
695 Simulation Methods. *Journal of Water Resources Planning and Management*,
696 114(3), 276–294.
- 697 Walski, T. M., Gessler, J., and Sjostrom, J. W. (1990). Water distribution systems:
698 Simulation and sizing. (M. Wentzel, Ed.)*Environmental Progress* (p. 321).
699 Chelsea: Lewis Publishers.
- 700 Woodward, M., Gouldby, B., Kapelan, Z., Khu, S.-T., and Townend, I. (2011). Real
701 Options in flood risk management decision making. *Journal of Flood Risk*
702 *Management*, 4(4), 339–349.

- 703 Wu, W., Simpson, A. R., and Maier, H. R. (2010). Accounting for Greenhouse Gas
704 Emissions in Multiobjective Genetic Algorithm Optimization of Water
705 Distribution Systems. *Journal of Water Resources Planning and Management*,
706 *136*(5), 146–155.
- 707 Zhang, S. X., and Babovic, V. (2012). A real options approach to the design and
708 architecture of water supply systems using innovative water technologies under
709 uncertainty. *Journal of Hydroinformatics*, *14*(1), 13–29.
- 710 Zheng, F., and Zecchin, A. (2014). An efficient decomposition and dual-stage multi-
711 objective optimization method for water distribution systems with multiple supply
712 sources. *Environmental Modelling & Software*, *55*, 143–155.
- 713