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ROBUST DESIGN OF WATER DISTRIBUTION NETWORKS FOR A PROACTIVE RISK AND UNCERTAINTY MANAGEMENT

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submitted to the Faculty of Sciences and Technology of the University of Coimbra
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Abstract

Water supply systems are crucial infrastructures in every modern society. In the last three decades the optimal design of these systems has been studied by a great number of academics and water industry professionals. However, most of these studies, consider future as predefined and working conditions perfectly known. This simplification leads to solutions which although optimal for the imposed conditions, may perform badly if reality turns out to be considerably different. In real world the working conditions can be disturbed by different types of situations such as, pipe breaks or tank failures, energy supply interruptions or changes in demand. Only a proactive attitude towards risk and uncertainty can deal with these aspects from the design phase until the end of the life cycle of the different components. Decision makers have to decide how these infrastructures should be planned and operated to cope with uncertain future situations. Researchers can provide help in finding and justifying good solutions, through the investigation of optimization tools.

The main contributions of this work are the decision-aid tools developed for the optimization of design and operation of water distribution networks capable of dealing with risk and uncertainty, thus being able to find more robust and reliable solutions. Water systems are costly and it is difficult to change physical component conditions without making large investments. When planning is considers future uncertainty, it is possible to obtain better solutions for a long planning horizon.

In the initial chapters, this work provides some insight into concepts and definitions regarding water distribution systems, as well as a comprehensive state of the art on

optimization techniques and on decision support approaches. Two optimization tools are also presented: the single-objective and multi-objective simulated annealing optimization methods.

Decision-aid tools are then proposed. A robust optimization model for the optimal design of water supply systems operating under different circumstances is shown first. The results show that robustness can be included in several ways and for varying levels of reliability. The inclusion of robustness considerations leads to more reliable designs, while at the same time results in small cost increases.

This is followed by a group of three different decision-aid models based on a real options approach, which constitute the main scientific contribution of this thesis. The first optimization model based on real options is used for the optimal design and operation of water distribution networks considering various possible future uncertainties. The results of this its implementation on a water network show that building flexibility into the decision strategy enables an adaptive approach to be taken that can avoid future problems with network capacity. The second optimization model is proposed to optimize water distribution networks taking into account environmental impacts associated with the installation and operation of water distribution networks. A methodology is established to compute these environmental impacts based on the embodied energy of the different materials used during the construction of water networks. The third model involves a multi-objective optimization approach to the optimal design and operation of water distribution networks considering conflicting objectives. The achieved results prove the capacity of the approach in dealing explicitly with conflicting objectives, with environmental impacts and with future uncertainty. Subsequent to the review and discussion of these proposals, it is presented a set of conclusions and suggestions for future work.

Resumo

Os sistemas de abastecimento de água são infraestruturas cruciais para qualquer sociedade desenvolvida. Nas últimas três décadas, o dimensionamento otimizado destes sistemas tem sido estudado pela comunidade científica e pelas próprias indústrias de abastecimento de água, usando valores de referência para as condições de funcionamento e operação no futuro. As soluções ótimas obtidas em tais condições poderão funcionar inadequadamente se a realidade vier a mostrar-se consideravelmente diferente do previsto. Em condições reais, os sistemas de abastecimento podem ser expostos a situações críticas de operação como a rotura de condutas e reservatórios, a falta de energia ou alterações drásticas nos consumos. Apenas uma atitude proactiva que considere os riscos desde o início do projeto até ao final do ciclo de vida das redes permite lidar com situações de incerteza. As entidades que gerem estas infraestruturas são responsáveis pelo planeamento e operação das redes devendo agir no sentido de mitigar os riscos. Porém os investigadores podem auxiliar a justificar e a tomar boas decisões através do desenvolvimento de ferramentas de otimização.

A contribuição central deste trabalho encontra-se nas ferramentas de apoio à decisão desenvolvidas para a otimização do dimensionamento e operação de redes de distribuição de água capazes de ter em conta a incerteza e de encontrar soluções robustas. Trata-se de infraestruturas onerosas em que, uma vez construídas, dificilmente se consegue alterar as suas condições físicas sem incorrer em grandes investimentos. Considerar a incerteza no processo de decisão permite definir soluções fiáveis para um longo horizonte de projeto.

Nos capítulos iniciais, este trabalho refere alguns conceitos e definições relativos a redes de distribuição de água. É realizado o estado da arte sobre técnicas de otimização e metodologias de apoio à decisão. São também apresentados dois algoritmos de otimização,

que posteriormente serão aplicados à resolução dos modelos propostos: um algoritmo baseado no método de recozimento simulado para resolução de prolemas uni-objetivo e um outro algoritmo baseado no método de recozimento simulado para problemas multiobjectivo.

De seguida são propostos modelos de apoio à decisão passíveis de serem usados para melhorar as soluções a implementar no âmbito das redes de distribuição. Primeiro é descrito um modelo de otimização robusta de sistemas de distribuição de água sujeitos a diferentes condições de operação. Os resultados indicam que a robustez pode ser incluída de formas diferentes e com diferentes níveis de fiabilidade, através de pequenos incrementos nos custos.

Seguidamente é proposto o contributo principal deste trabalho: um grupo de três modelos de apoio à decisão baseados no conceito de opções reais. O primeiro trata da otimização do dimensionamento e operação de redes de distribuição de água considerando a incerteza ao longo da vida de funcionamento da rede. Os resultados mostram que a inclusão de flexibilidade no processo de decisão possibilita definir soluções mais adaptáveis à medida que surge nova informação e possibilita evitar problemas de falta ou excesso de capacidade hidráulica da rede no futuro. O segundo modelo de otimização é construído para permitir obter soluções para os problemas de otimização de redes, quando se incluem, no processo de decisão, os impactes ambientais associados à respetiva instalação e operação. Para tal, é detalhada uma abordagem para o cálculo dos impactes ambientais baseada na energia incorporada nos materiais utilizados na construção de redes. Por fim é apresentado um modelo de otimização multiobjectivo para o dimensionamento e operação de redes. Neste modelo são também considerados os impactos ambientais para determinar um conjunto de soluções eficientes. Os resultados atestam a capacidade do modelo em lidar explicitamente com objetivos conflituantes e além disso ter em conta os impactes ambientais e a incerteza no processo de decisão. Na sequência da análise e discussão das propostas referidas, é apresentado um conjunto de conclusões e sugestões para trabalhos futuros.

List of Contents

List of Figures

List of Tables

ROBUST DESIGN OF WATER DISTRIBUTION NETWORKS FOR A PROACTIVE RISK MANAGEMENT

Chapter 1

Introduction

This chapter presents the main motivation of this study, shows the introduction of the problem and explains the research objectives*. It concludes with a description of the thesis structure.*

Keywords: water dependence, water supply systems, decision support

1.1 Motivation

Water and its life-giving chemistry have supported all known forms of life on Earth for millions of years. Over 70% percent of the Earth's surface is covered with water, and it exists naturally both as liquid, gas and solid forms in our environment. Water has been studied since ancient times and is the most common liquid on our planet. However, potable water is relatively scarce and it is necessary to preserve it. Only 1.3% of the Earth's water is easily available to humans, the other 98.7% is found mainly in oceans and in the polar ice caps. The geographic distribution of water is irregular and rarely exists as desired in the region where it is required.

Population growth and groundwater depletion represent the two most significant dangers to global water scarceness. With the population increase, industrial and agriculture development, water consumption increases rapidly, and it becomes progressively more difficult to satisfy the water needs of all the sectors. Much of the population growth and economic development experienced in the last fifty years has been supported by water reserves. These nonrenewable reserves are being consumed at unsustainable rates. For example, the usually called Great Man-Made River is a water system that supplies 6,500,000 m^3 of water per day from an aquifer to the territory of Libyan (Mansor and Toriman, 2011). Some experts argue that this fossil aquifer could be depleted of water in as soon as 60 to 100 years. Besides the aforementioned problems, there are also serious pollution problems, caused mainly by man. The main sources of water pollution are domestic sewage, industrial and agro-livestock, intensive agriculture, soil leaching, waste and saline intrusion. Thus, it is imperative to promote sustainable water use based on minimizing the waste of water and on protecting the available water resources. The equilibrium of the planet depends on the conservation of water and its cycle, so its protection is a common duty.

Water dependence is intrinsically related with society's development. In history it is easy to find civilizations that prospered around rivers and lakes. Even in the early days, there were large metropolises whose success was in part due to the easy access to water. According to Undp (2006), over 1.4 billion people currently live in river basins. The opposite can also be perceived. In the Middle East and North Africa water is scarce and urban development is weak.

In the last centuries the development of societies occurred so fast that it is seems impossible to think about the future without uncertainty. Water consumption increased at more than twice the rate of population increase in the last century. As the world becomes more developed, the amount of domestic water used by each person (demand per capita) is expected to rise significantly. Climate changes will probability decrease the resources of freshwater. Thus, the effective management of these complex and enormous systems has become a very challenging task. Under all of these problems and uncertainties it is imperative to find tools capable to support the decision making on water infrastructure development and management. Due to the variability of real life working conditions and constant changes in configurations and operation of water supply systems, it happens quite often that these systems end up working under conditions different than the ones planned for their life horizon. For example, many water supply systems in developed countries operate in low efficiency modes due to the reduction of water consumption in the last years. On the other hand, in developing countries, almost all water suppliers are making efforts to provide a proper service due to the rapidly increase of water consumption.

Blumenfield *et al*. (2009) argue that by 2025, 1 800 million people will be living in countries or regions with absolute water scarcity, and two-thirds of the world population could be under stress conditions. However, there are two different types of water scarcity, **physical water scarcity**, when there is not enough water to meet our needs, for example in arid regions, and **economic water scarcity**, when human institutional and financial capital limit access to water even if water is available in nature for human needs. For this second type of water scarcity, the problem can be solved easier than in the first case.

Of all community services, provision of potable water is probably the most vital. The need for a robust analysis of technical, economic, environmental and social aspects of water supply systems represents the main motivation for this study. Modern planning of water supply systems implies using advanced operations research methods and computing tools to optimize and control water systems. In order to identify supportable planning decisions for these complex systems, it is necessary to have tools able to generate and examine different possible alternative solutions and chose the best ones according to guide lines established by decision makers. Two main approaches, namely robust optimization and real options, will be developed in this thesis based on the same optimization heuristic but used to solve different problems. These approaches will help decision makers to find the trade-off among different objectives, allowing them to deal with costs, risk and uncertainties more thoroughly. These approaches will contribute to the development of more reliable water supply systems and will bring these one step further in dealing with new challenges of the future.

1.2 Main problems of interest and objectives of the study

The goal of this thesis is to develop optimization tools to the design and operation of water supply networks under risk and uncertain situations. These infrastructures are responsible for the collection, transmission, treatment, storage and distribution of water. These systems appeared more than 5 thousand years ago with the Egyptians, which built water systems to supply the pharaoh palaces with water from the Nile river. Probably, the most notable of ancient water systems are the aqueducts built by the Romans. In Rome these aqueducts ended at distribution reservoirs, from which the water was transported to public baths or fountains. These channels were build using stone, brick and rough concrete. During the middle ages there was no notable progress in the water distribution field. In the 19th century the use of cast-iron pipes, capable of withstanding high pressures, and the use of steam engine water pumps, made it possible to rapidly increase the number of communities with access to drinking water, supplied directly to individual homes.

Nowadays, water supply systems are dispersed for wide areas and it can be said that in developed countries almost all the citizens are supplied with water. One part of the system is the water distribution network, which is constituted by pumps, pipelines, storage tanks, valves and other singularities. This work will focus on this part of the systems. Networks must deliver adequate quantities of water at acceptable pressures. The water distribution network is the most expensive part of the water supply system. Normally the pipelines are placed within the public ways so that service connections can be made for all potential customers. The materials used in distribution pipes can be asbestos cement, cast iron, ductile iron, plastic, reinforced concrete or steel.

The design of these networks depends on different aspects. Water supply systems analysis should take into account different aspects of the future. Therefore, the integration of different objectives and criteria in the development of alternative water supply planning options is the main problem to be dealt with. In the real world, water systems management varies according to different features. There are different water needs, variable water resources, numerous social, environmental and political preferences and different economic and technical abilities. This leads to the realization of many different kinds of solutions. Furthermore, the increasing criterions for water quality and operation, as well as factors such as savings due to economies of scale, increasing reliability, and simpler quality control, make the aggregation of the water services a solution to be taken into account.

Many kinds of approaches for the analysis and design of water systems have already been developed, but very few have been practically applied (Walski 1995). Since the early studies of Alperovits and Shamir (1977) and Walski *et al.* (1988) many different tools have emerged in the literature. The development of approaches that take into account the uncertainty in the water supply systems design and operation is intended to be the main practical contribution of this work.

In addition to the ever increasing spatial dimension of water supply systems, their high complexity poses even greater problems to their operators and managers. Water supply networks are typically designed for periods of 20 to 60 years and very often operate during much longer time. The physical changes in the systems characteristics due to corrosion, deposition, and others, additionally contribute to the uncertain environment in which the network works. Therefore, a huge interest exist for the development of tools able to lead to more robust water supply systems planning, design and operation, and able to provide alternative options, that can be better accommodated for different possible development future scenarios. In particular, the consideration of robustness in the water supply system design is an important issue that will be addressed in this study.

There are many recent adjustments in the water supply sector. High water quality standards and greater environmental awareness are some of the forces that imply an increase of the systems efficiency and environmental impacts attenuation. This study aims to include the environmental impacts on the decision making process. Besides, water users have high expectations on the well-functioning of water systems. The traditional design and operation, actually existing, isn’t able to take into account the vulnerability of these infrastructures. The inclusion of uncertainty considerations in the development of alternative water supply systems planning, design and operation options is another important problem that this study aims to address.

It is very important to improve the scientific knowledge in the decision support field of water supply systems. The new challenges of the future require advanced tools capable of dealing with highly complex and extremely uncertain issues. Some techniques will be presented in this work, with the main objective of determining good solutions for water supply systems design and operation.

1.3 Structure of the thesis

This thesis is subdivided in 8 chapters. After the introduction, presented in this chapter, the theoretical foundations and literature review are described in chapter 2, and the developed optimization tools in chapter 3. Chapter 2 aims to explain the context of this work and familiarize the reader with the developed approaches. A state of the art in this field is also presented. Chapter 3 focuses on the optimization tools that were developed to solve the optimization models. The four main chapters, from 4 to 7, are all presented in scientific paper format. The paper of chapter 4 has already been published. The paper of chapters 5 has been submitted and it is conditionally accepted and the papers of chapters 6 and 7 are expected to be submitted soon. According to this structure, all of these chapters have practically the same structure composed by an introduction, the literature review, the model formulation, the case study, results and conclusions. According to this, it is inevitable to have some repetitions through the chapters. However, the order of the chapters tries to provide a consistent connection between the subjects.

Chapter 4 consists on the first approach adopted to solve the optimal design problem under uncertainty through a robust model. The model is aimed to determine a robust solution that works well under different scenarios. The focus of this work was also to find some different forms to include robustness in the optimal design of water supply systems. Starting from the work of Cunha and Sousa (2010), the first step was understanding that the robustness should not only be dealt with by enlarging some pipe diameters, because pipe cost increases significantly with the diameter, and thus this additional capacity is quite expensive. Also, larger diameters lead to low velocities and high water residence times, neither of which is desirable in terms of water quality and safety. This work proposes a different approach by adding a pumping station to be used like a contingency infrastructure. The optimization model is presented and tested on 2 case studies. The results are exposed and some comparisons are made. Finally, conclusions are set out.

Chapter 5 introduces a real options tool. This new approach will be the main innovative contribution of this work and will be used in the forthcoming three papers. The first chapter explains how real options should be used in the water distribution optimization field and also the reasons for using this approach in the water supply field. An overview of the approach is made. This is followed by a case study to explain the method, and a decision model is built. The results and comparisons are drawn against traditional approaches. Lastly, the conclusions are systemized.

Chapter 6 proposes a real options approach that, while taking into account environmental impacts, tries to find appropriate flexible solutions for the design and operation of water distribution systems. This work describes a methodology to compute environmental impacts based on the quantities of carbon dioxide emissions. During construction, carbon emissions are related to pipes and singular elements as reservoirs, pumping stations, accessories and others that influence the carbon emissions. Furthermore, the energy consumption also produces carbon emissions of electricity generation. In the introduction, a literature review is presented, as well as a methodology to compute the carbon emissions of a water network. Next, the decision model is built. Thereafter, a case study is developed to analyze the resolution of the application of the methodology and the results are shown. Finally, some comparisons are made and conclusions are systemized.

In chapter 7 a multi-objective model for the optimal design of water distribution networks considering environmental impacts and future uncertainty is developed. The results determined by the single objective optimization tool developed for chapters 4, 5 and 6 cannot deal explicitly with multiple objectives. A multi-objective optimization model based on simulated annealing heuristic is developed to identify solutions that are a good trade-off with conflicting objectives. This work incorporates the real option approach to deal with uncertainty and considers also the carbon emission cost related to the construction and operation of water networks. After the introduction, the multi-objective model is presented and some concepts are clarified. Then, the results are set out and the conclusions are drawn.

Finally, Chapter 8 presents the conclusions of this work and summarizes the work done within the scope of these thesis as well as some future trends.

As already been mentioned, this document is written according to scientific papers. Thus, it is essential to refer the publications that resulted from the work developed during the PhD. The paper presented in chapter 4 is reviewed and published in the Drinking Water Engineering and Science Journal. Chapter 5 presents a paper submitted to the Journal of Water Resources Planning and Management and is conditionally accepted. Chapters 6 is planned to be submitted to journal of Environmental Modelling & Software and lastly chapter 7 is planned to be submitted to Journal of Hydroinformatics.

Beyond the publications of the papers in scientific journals, during the PhD presentations and discussions of the research have been made in national (Portuguese) and international conferences.

Chapter 2

Literature Review and Theoretical Foundations

The aim of this chapter is to provide foundations and the definition of terms that will be used in this work. First, a description of the water supply systems is made. Then, a state of the art on the optimization techniques and on the decision support approaches is explored.

Keywords: water supply systems, decision models, simulated annealing

2.1 Water supply systems

Some infrastructures are fundamental to societies. Water supply systems are one of those, and are generally defined as multi-purpose networks for the collection, transmission, treatment, storage and distribution of water to domestic, commerce, industry and agriculture, as well as for some public needs, such as firefighting and street flushing. Water utilities intend to grant that clean water with adequate pressure is delivered to customers. Nowadays water distribution networks are complex systems that require high levels of investment for their construction, operation and maintenance. Thus, it is imperative to use advanced tools in order to identify sustainable planning decision for these intricate systems, and to examine different possible alternative options, in order to select the ones that are better according to some predefined management objectives.

2.1.1 Main characteristics

Although the dramatically variety of sizes and the complexity of water supply systems, all of them have the same fundamental objective, that is to deliver energized water. These systems are normally constituted by various components interconnected and with specific functions. The main elements are represented schematically in Fig. 2.1:

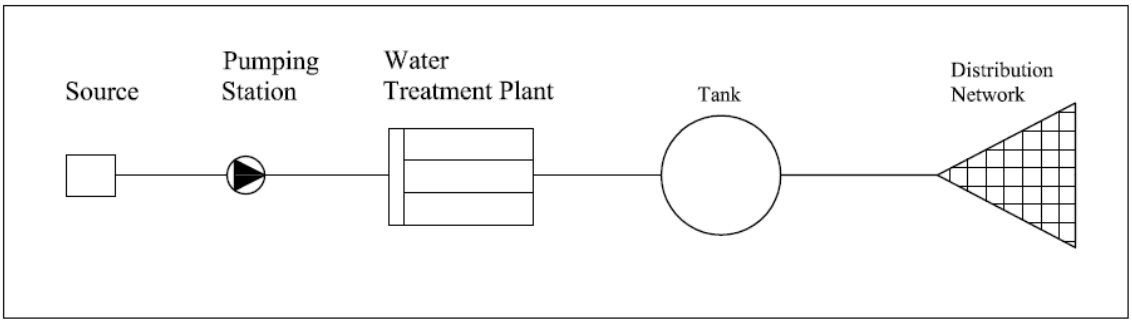

Figure 2.1: General scheme of water supply systems

In general, water systems are established by the following processes:

- **Extraction and transport** - water is retrieved from a source and is normally transported to water treatment plants;
- **Treatment** - water is treated to satisfy quality standards. Some water treatments typically used are: mixing, flocculation, sedimentation, filtration and disinfection.
- **Storage** - water is stored due to the variability of daily demand, as well as to create reserves for fire fighting and failures;
- **Distribution** - water is distributed through the area in a way to guaranty adequate flows and pressures to costumers. The distribution network is constituted mainly by pipes, valves, pumps and tanks.

The main objectives of water transport and distribution networks are to guarantee the supply of adequate quantities and the maintenance of water quality through adequate pressures and velocities. The latter is done by keeping pipes always in pressure, to reduce risks of external contaminations, and by keeping adequate velocities, to reduce the retention times. The installation of pipes to transport and distribute water requires the major investment in water systems. These pipes can be classified as:

- **Trunk pipes** – to transport water from water treatment plant to the distribution area;
- **Secondary pipes** – to form the basic links of the distribution system, which normally only provide service connections for large consumers;
- **Distribution pipes** – to link the secondary pipes to the various costumers. These links have numerous service connections and valves to guaranty the adequate supply.

Storage facilities are part of the water systems. They should be located in favourable places, this is, more elevated than the consumption points. Tanks serve to meet variable demand to the network, to guarantee reserves to fire fighting and failure emergencies, and to maintain nodal pressures more stable. The selection of the tanks position depends from topographical conditions of the network, pressures, costs, climate conditions among others. The required volume depends of the volume established for emergencies, on the daily demand pattern and on the pump operation schemes. Tanks can be built underground, on the ground level or elevated.

Pumps add energy to water. These elements are used in networks where additional pressure is required. Centrifugal pumps are the most common used in water systems and they can operate with fixed or variable velocity of motor revolutions.

Variable speed pumps are able to follow the demand pattern and retain stable pressure. These are used for cost-saving purposes.

Large water supply systems are usually a very complex agglomeration of many different parts, having more than one source, treatment units and multiple pumps and tanks across the network. The distribution network can be branched, semi-looped or looped, as represented in Fig. 2.2. In semi-looped and looped systems, there are some different paths that can transport water between two nodes. Looped networks are preferred because they provide additional redundancy. However, the branched networks are much more economical. Haimes (1998) defines redundancy as the capacity, information, resources, time, or components, such as backup power supplies, pipes or pumps, added to the system beyond those needed for normal operation.

The additional redundancy provided by looped networks means the existence of more than one path to transmit water between two nodes. The level of redundancy is given by the number of additional paths able to supply a node. From figure 2.2 it can be seen that the branched network doesn't have any node with redundancy, the semi-looped network has nodes 3, 7 and 8 with redundancy, and the looped network has all nodes with some level of redundancy.

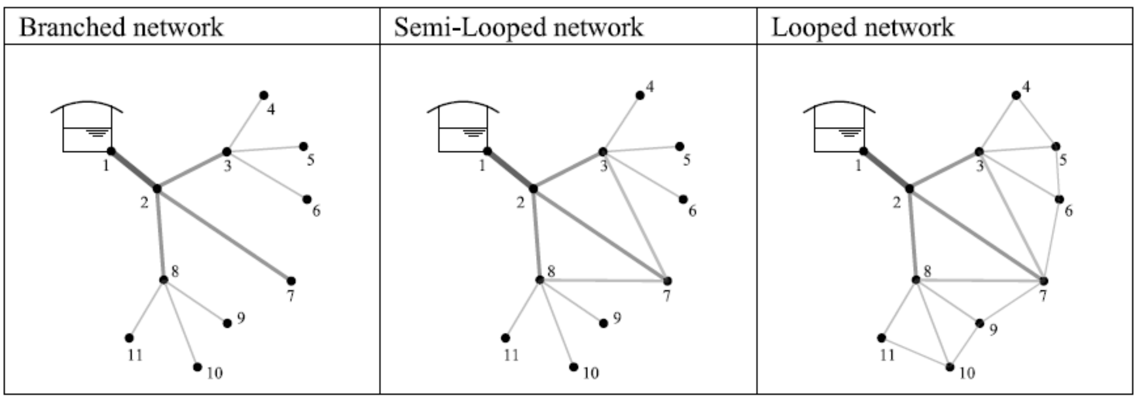

Figure 2.2: Branched, Semi-Looped and Looped network

In order to transport water to consumers, pipes should have enough hydraulic capacity. The flow is determined considering the hydraulic characteristics of the network as well as the energy inputs. The flow in the network is dependent of many different physical properties of the infrastructure. Furthermore, there are some characteristics that change during the system's life time, such as the increase of friction coefficients in pipes due to corrosion and deposits, or pumping stations and valves deterioration. These changes should be taken into account during the systems planning.

As the demand for water increases, it is necessary to find new resources of potable water. There are several sources of water available in nature: surface water in rivers and lakes and groundwater are the most common sources. But there are areas in the world where these sources are unavailable and it is necessary to look for new origins of water. Some of alternative sources are salt water, frozen water, reuse of waste water and catchment of rain water. Water availability is one of the main forces that influences the infrastructure planning. The variation of the availability and quality of water resources makes water planning very uncertain.

Water supply systems have normally two main requirements: they have to deliver enough water quantity with quality and they have to satisfy fire flow requirements. Furthermore, water systems need to be reliable, considering that they must operate during 24 hours a day and 365 days per year. Haimes (1998) defines reliability as the likelihood that the system performs its indeed functions under normal conditions, and when it fails, it experiences a "safe failure", by other words, the systems fails without causing dire consequences. The design of water supply systems usually follows these basic steps:

- Estimate the nodal demands;

- Establish the network configuration;
- Select the commercial pipe diameters to be used and materials;
- Analyze the hydraulic performance of the proposed solution;
- Modify the configuration and/or the diameters as a function of the results obtained by the hydraulic analysis;
- Repeat the process until a satisfactory solution is found.

There are many factors that need to be considered when planning and designing a water network or water service. Fig.2.3 shows a group of these.

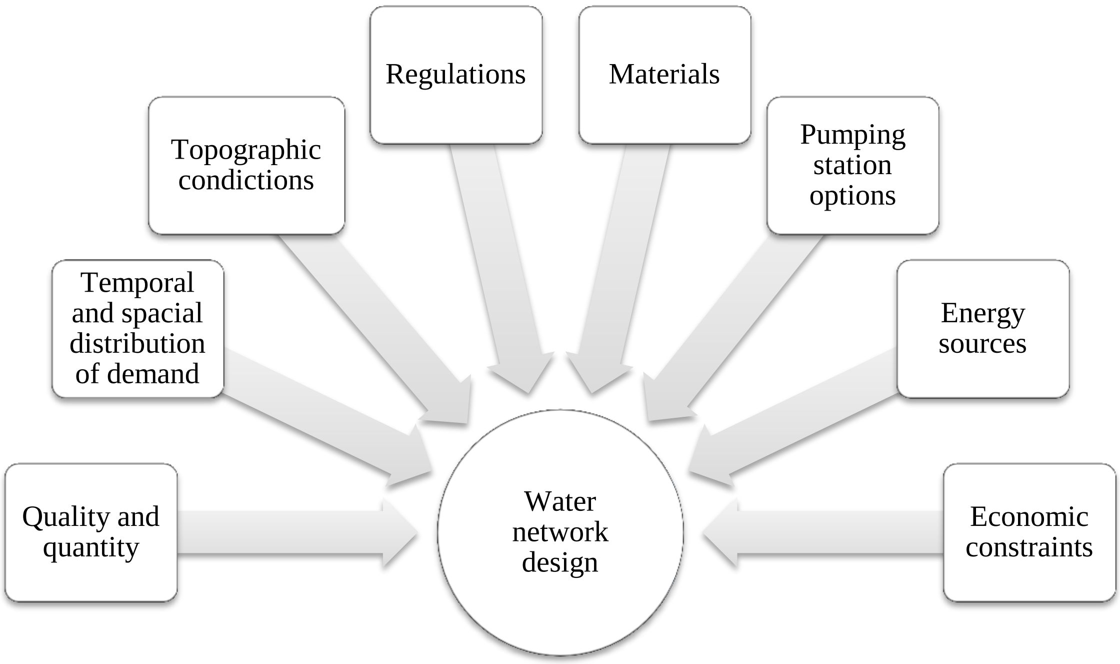

Figure 2.3: Water network design factors

The consideration of all factors presented in Fig. 2.3 is a very challenging task. There are some tradeoffs that need to be taken into account in the design process. Different factors have a significant impact on the network hydraulic design. For example, opting for a larger diameter, will offer more capacity in supply but implies a substantial increase in investment costs. Overdesigning some network components can only be justified by estimating the potential high losses due to extreme situations leading to the interruption of water supply.

2.1.2 Hydraulic models

The simulation of real world through computer models has many advantages. Models are defined as theoretical constructions that try to represent real life systems and/or processes through a set of variables and a set of logical and quantitative relationships between them. The hydraulic models have applicability in different fields: planning, project and operation of water supply systems, and its correct application can provide innumerous advantages to technicians. Today it is possible to model the performance of networks during long periods using dynamic simulation. Simultaneously it is possible to model the water quality through determining concentration of the disinfectants such as chlorine and recognize the paths where in water travels inside the system as well as the residence time.

Determining flows and pressures in water distribution systems involves solving a great number of nonlinear equations simultaneously. Until recent advances in computer science/software these calculations were impossible.

Since the early years of the 20th century, some techniques emerged to simulate the hydraulics of water systems. Looped systems required tedious iterative calculations and heavy use of slide rules. Hardy Cross (1936) established a systematic tabular process for computing system hydraulics. The first computer solutions of network problems were done on analog computers, with electrical elements being used to simulate water pipe networks. Digital computers were first used to solve network problems in the early 50s (Walski *et al*. 2003).

Initial hydraulic analysis approaches were based on automating the Hardy–Cross method, whereas later methods took benefit from the computer's facility to solve matrix problems. These models were later extended to deal with more complex hydraulics including pumps, control valves, and extended-period simulations. The Softwares that exist nowadays can be used for different goals, as shown in Fig. 2.4:

Figure 2.4: Areas where hydraulic software is used

The use of hydraulic analysis simulation software spread out in the research and industry field, mostly due to the exponential increase of computational capacities. Nowadays, a number of packages are free available allowing adaptations for the specific requirements, not only for scientific community, but also to water companies and industry. Popular packages such as EPANET, Rossman (2000), enable the implementation of mathematical models of a water distribution networks that combine the physical laws governing the networks with the equations that relate pressure and flow for each operational component.

2.1.3 Vulnerabilities

There is a growing concern about how to increase the security of fundamental systems to societies. Water supply systems are highly vulnerable infrastructures and a vast body of bibliography can be found in this area. The next paragraphs resume some of these works.

Haimes (1998) believes that the main challenge that science has to tackle in the design and operation of infrastructures in this third millennium, is the development of tools and technologies that can keep facilities such as these in operation. The Author feels that societies' living standards have improved considerably, but even so the provision of services relies to a great extent on infrastructure, and the risks and vulnerability to failure during operation have grown. Danneels and Finley (2009) see the events of September 11 as the driving force behind the analysis of the vulnerability of infrastructures. In the wake of this attack the USA passed a law on public health security that forced water supply systems, serving more than 3 300 consumers, to be assessed for vulnerability and risk. The RAM (Risk Assessment Methodology) was developed. This can specify the measures to be implemented to lessen vulnerabilities and thereby increase the security of infrastructure components. Haimes *et al*. (2012) observe that water supply systems' vulnerabilities have to be assessed not just for a particular point in time, but for their entire working life, since their nature and level are changing all the time. The authors paid special heed to terrorist attacks since there is a vast amount of literature about natural disasters and relative little about terrorist attacks. They divide possible terrorist threats into water supply systems into physical, chemical/biological and cyber threats.

According to Matalas (2005) the systems' vulnerability can be reduced by implementing security measures such as increasing redundancy, robustness and system resilience. The author also says that there has been little experience in dealing with terrorist attacks compared with natural disasters, and that they tend to be isolated incidents with unforeseeable consequences. Any decisions on preventing such events are taken in a state of complete uncertainty.

It is observed that there are a great many extreme situations that can affect water supply systems and they can be broken down into natural and human events; these last ones can then be subdivided into technological and human failures, and terrorist attacks. An action that could cause immense damage to public health is the chemical contamination of water supply systems. Meinhardt (2005) notes that deliberate contamination of water supply systems by terrorists could have very serious consequences because most staff operating the equipment do not have the sort of knowledge to recognize and assess possible water contamination and the author provides information that enables staff to recognize, control and prevent bioterrorist attacks. In terms of natural disasters, the Institution of Civil Engineers (1995) describes a huge number of disasters and their harmful impact on water supply systems.

2.1.4 Risks

The risk of water supply systems to different disasters can be calculated based on the probability of a disaster occurring and its likely consequences. But there are still unforeseeable events whose probabilistic distribution cannot be determined. Several ways of structuring methods to manage risk and uncertainty in systems have emerged recently. One is the risk wheel outlined by PLANAT - National Platform on Natural Hazards, Schweiz (2003).

Ezell *et al*. (2000a) describe a method for including risk probability analysis in water supply systems called “Infrastructure Risk Analysis Model” (IRAM). It gives the average figures for calculating the critical measures that are relevant and actually required for the assignment of resources to enhance the system’s security. This method has four stages: first, the risks are identified; second, possible scenarios are worked out; third, the system’s security is established and expected losses for each scenario are calculated; fourth, alternative damage mitigation measures are developed, the risk model is reappraised and the Pareto boundaries of the mitigation alternatives determined. In another paper, Ezell *et al*. (2000b) applied the method to a water supply systems to show how it can be used to assess the risk and determine the use of scarce resources to improve the security of the system.

In the context of terrorist attacks, Tidwell *et al*. (2005) describe a model based on latent effects, i.e., events, occurrences, conditions or behaviors that do not necessarily cause an immediate problem but which do so when subsequently combined with other occurrences, conditions or behaviors. These are pinpointed by breaking down the threat into different decision levels and so that it is easier to see the basic events that contribute to the characterization of the threat. The probabilities of success or failure at the decision levels are then quantified so as to find the probability of the threat actually occurring.

Kunreuther *et al*. (2002) propose a method that uses cost-benefit analysis to assess the various damage mitigation measures applied to critical infrastructures subject to earthquakes. A systematic assessment and decision procedure comprising the following steps is used:

- Specifying the nature of the problem, alternative options and interested parties;
- Determining the direct costs of the mitigation alternatives;
- Determining the losses with and without mitigation alternatives;
- Calculating the attractiveness of the mitigation alternatives and choosing the best of them.

The authors use this method on a water distribution system; four possible seismic scenarios are considered, and two alternatives: keeping the system unchanged and strengthening all the system's reservoirs to be able to withstand severe seismic events.

Chang (2003) published a paper on the application of a life-cycle cost analysis usually employed to manage infrastructures, and in this case extended to assess the costs and benefits of seismic disaster mitigation for critical infrastructures. As most studies in this area use cost-benefit analyses that do not consider the inevitable wear and tear of infrastructure's component in the course of their working life the author uses life-cycle cost analysis, which implicitly considers this factor. This analysis considers both the costs/benefits of seismic mitigations and the benefits of these actions in reducing maintenance expenses.

Water supply systems cannot be regarded independently when we are looking at their vulnerabilities or reasons for operating failures. The systems depend on other infrastructure such as the electricity grid and telecommunications networks. Haimes (2005) notes that a new dimension of vulnerabilities has emerged in the wake of the rapid spread and integration of telecommunications and computer processes in the management and operation of systems that link the infrastructure to one another in a complex network of interdependencies. It is therefore necessary to quantify them so as to assess and deal with potential threats.

Haimes and Horowitz (2004) describe a methodology based on Hierarchical Holographic Modeling in a study on infrastructure interdependencies. Haimes and Jiang (2001) developed the Leontief-based infrastructure input-output model that can quantify internal and external links between infrastructures. This model considers critical infrastructures connected to one another and globally as a complex and finds the risks of its subsystems suffering operation failure. It can be implemented in an optimization model, taking the reduction of the risk of operating failure as the objective function and the pre-established amount of resources to be used as the main restriction.

Dueñas-Osorio *et al*. (2007) devised a method to analyze the interdependencies between an electricity grid and a water supply system. In it the response of the networks to disruption is measured in terms of the effect that the removal of an element from the network has on overall connectivity. The interdependencies between the two networks are modeled by establishing the degree of connection through a spatial proximity criterion. The dependence of the water supply systems on the electricity grid stems from the need for power to operate the pumping stations, water treatment plants, and so forth. Having analyzed the networks in a case study the authors found that the water system is highly vulnerable to stoppages of the main elements in the electricity grid, which indicates that redundancy can be used to identify the weakest points in the networks.

2.1.5 Environmental impacts

It is commonly accepted that engineering infrastructures as water supply systems cause environmental impacts on the full range of components as water, land, air, ecology and noise.

Traditional methods for optimizing water supply systems deals with concerns like cost minimizations and pressure and velocity constrains. These concerns are important to water utility at a local level, but practitioners are beginning to recognize that environmental impacts should also be included in the decision process at a global level. Therefore, concerns with material, energy use and carbon emissions associated with the production of network components and their continued operations should also be incorporated in the optimal design of water distribution systems.

In the literature it is possible to find different methods to incorporate environmental issues into the design of water infrastructures. Dennison *et al*. (1999) use a **life cycle assessment** method to compare the environmental impacts of different pipe materials. A process based on life cycle assessment is defined as the environmental impacts of a product over the entire period of its life cycle including, extraction, transport, manufactures, use and final disposal (UNEP, 1996). Filion *et al*. (2004) also use an environmental input-output life cycle assessment for the economical quantification of the environmental releases connected to material manufacturing and components used in water supply systems. Dandy *et al*. (2006) developed a multi-objective optimization program that incorporates sustainability objectives like life cycle costs, energy expenditure, greenhouse gas emissions, and resources consumption. The optimization program was applied to a real case study in Australia, where a comparison between the least-cost design with a sustainable design was made. The results demonstrate that the sustainable design had a lower cost, a reduced rate of material and energy use, and lower greenhouse gas emissions. Another approach was developed by Herstein *et al*. (2011) presenting an index-based method to assess the environmental impact of water supply systems. The index aggregates the resource consumptions, environmental discharges and environmental impacts in one unique value.

The research presented in chapter 6 of this thesis will exhibit a methodology developed to take into account the environmental impacts based on the carbon dioxide equivalent emissions. The construction and operation of the network are both considered to determine the direct and indirect carbon emissions of the water supply components.

2.2 Optimization models

Humans always have a great interest in optimizing the performance of systems that they use. Optimization models are used to find the best possible choice out a set of alternatives. A mathematical expression, usually known as objective function of a problem can be used to minimize or maximize some objective. The model is usually composed by constraints restricting out the values of variables. Each of the objectives to optimize is typically a measure of performance of the system and should be expressed as a function of the decision variables. If there is just one measure of performance (for example the construction cost) the model will be a **single objective model**. When there are several measures of performance, we have a **multi-objective model** in which two or more objectives functions need to be optimized simultaneously.

There are different optimization techniques that can be used according to the problem to be solved. Some of them permit finding the global optimum solution, with theoretic prove of convergence, but normally, in real world, it is impossible to know if the solution found is the best one.

Motivated by the need to improve the efficiency and reduce the associated costs of construction and operation of water systems, practitioners have progressively moved away from design based on experience in favor of automatic techniques.

A great amount of optimization techniques developed for water supply systems have been developed in the past few decades (Sacks *et al*., 1989) and several reviews of the bibliography in water distribution optimization are also available like the works of Lansey (2000) and Walski (1985). Regardless of the considerable development of research, optimization techniques have not been regularly accepted in practice (Walski 2001).

The optimal design of water networks has been mainly resolved as a single-objective least cost optimization problem with pipe diameters being the most common decision variables. This is a non-linear optimization problem due to the head loss constraints, and a discrete combinatorial optimization problem due to pipe diameter decision variables that are given by commercial dimensions. The enumeration techniques are unfeasible in real size network optimization problems. The size of the solution space (the total number of possible solutions to the problem) for the network optimization problem can be calculated as the number of possible discrete pipe diameters to the power of the number of pipes in the network. For instance, a network with 20 links and with 10 possible commercial diameters has 10^{20} = 100,000,000,000,000,000,000 possible solutions. It is thus impossible to analyze every single network alternative, even for small size networks. If several design measures have to be considered at the same time, such as robustness or environmental issues, the problem complexity also increases.

According to Walski (2001), multi-objective optimization approaches seems to be promising. However these techniques suffer from efficiency when compared to its single objective equivalent approaches. Typically, an enormous number of simulation runs are required.

During the life time horizon of water supply systems it is possible to distinguish among main management stages. The most often used approach was given by Jamieson (1981) and it is presented in Fig. 2.5.

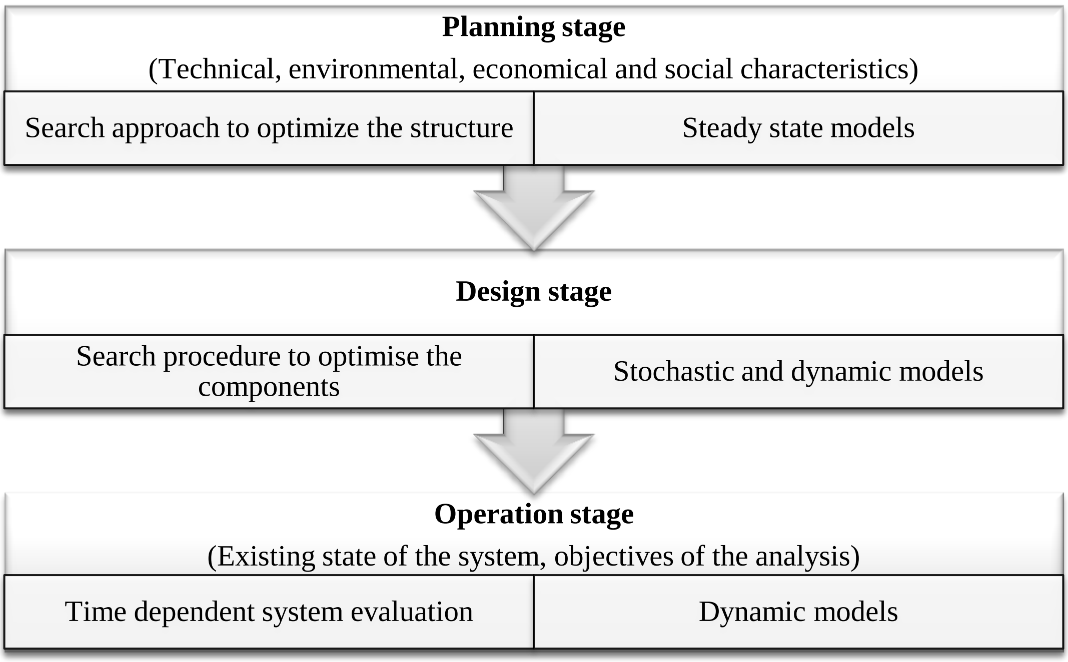

Figure 2.5: Approach to water systems management based on Jamieson (1981)

The management is subdivided in planning, design and operation stages. The planning stage focus on the systems structure, investment costs and the development of the resources. The design stage is focused on the cost minimization of components that satisfy the different kinds of constraints. The operation stage aims to minimize the systems operation costs, develop strategies for better maintenance, and to improve the systems performance.

Optimization models can be used in water supply systems to ensure low-cost solutions and high levels of performance and efficiency. During the last decades, much research has been made concerning methods aiming to obtain the optimal design of water distribution systems. These methods can be decomposed according to Fig. 2.6.

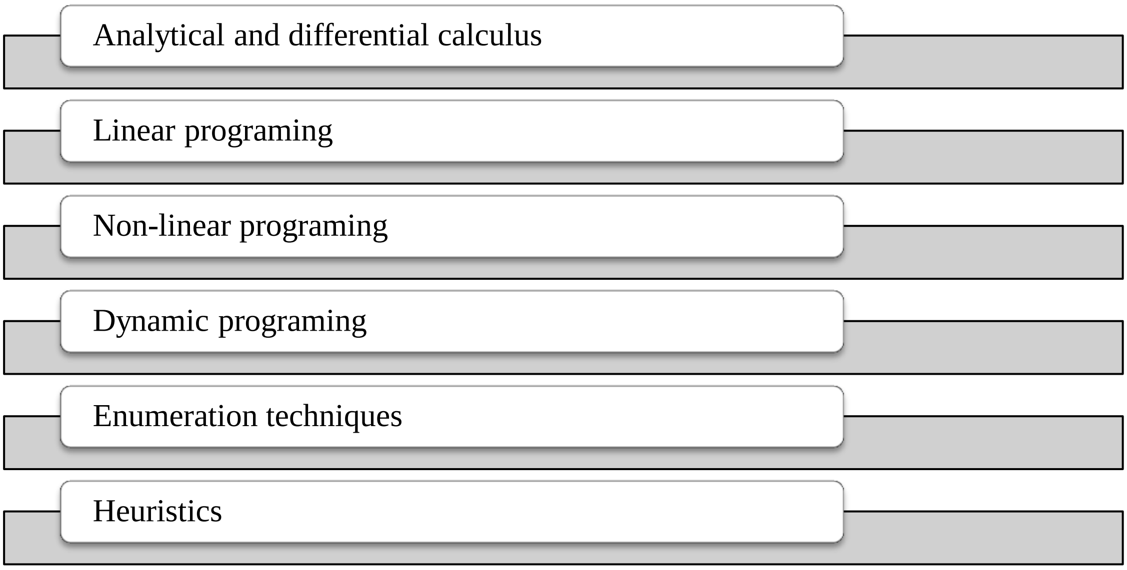

Figure 2.6: Methods for water networks optimization

Analytical and differential calculus are based on analytical solutions where the objective function is computed by its derivatives. The results are continuous diameters that need to be approximated to commercial diameters. This is an important disadvantage since by approximating the diameters, the solution loses its optimality. The work of Deb (1973) applies this method.

Linear programing methods have advantages due to the existence of commercial software’s that permit to obtain efficiently, the global optimum solution. However, in order to use linear programming in the optimal design of water networks, it is first necessary to simplify/transform the problem into linear functions, for example, to describe pipe costs and head losses in pipes as linear functions. This is a gross simplification to be made. This method was applied by Alperovits and Shamir (1977) and by Fujiwara *et al*. (1987).

In the non-linear programing area, Shamir (1974) presents a generalized reduced gradient demonstrated in Lasdon and Waren (1983), for the optimal design of water networks. Fujiwara and Khang (1990) present a non-linear programing method that has the capacity to avoid getting trapped in local optimum solutions.

Another class of methods is the dynamic programming, which is adequate to solve easily decomposable problems. This is the case of branched networks. In looped networks, this method can only be applied in small size optimization problems. The work of Vamvakeridou-Lyroudia (1991) developed a method applicable to looped networks.

The use of enumeration techniques to determine the global optimum solution for water networks can only be used for small dimension problems. If the solution space is large, some authors opt for restrict research to a small number of variables. The works of Gessler (1985) and Walski *et al*. (1988) use these methods.

Finally the last type of methods, are grouped in the usually called heuristics. Some of these techniques were developed specifically for the optimal design of water distribution systems problems. Tong *et al*. (1961) developed a method based on the equivalent pipe length with the objective to minimize the sum of the pipe lengths of the network. But some other methods surged to solve more general difficult optimization problems, the usually called modern heuristics. These types of methods are normally inspired on nature processes, they are global search methods and have the ability to avoid getting trapped in local optimum solutions. During the last decades, a great amount of research has been produced. In the next lines some of these methods are presented with more detail, namely, genetic algorithms, tabu search, ant colony and simulated annealing.

2.2.1 Genetic algorithms

Genetic algorithms are general purpose search techniques based on principles from the genetics and evolution mechanisms observed in natural systems and populations of living beings. This method can be studied in detail on the work of Goldberg (1989).

The paper of Goldberg and Kuo (1987) was the first work reporting the use of genetic algorisms to the optimization of a pipeline. Since them Dandy *et al.* (1996), Savić and Walters (1997) and Wu and Simpson (2001) has demonstrated the capacity of this method to find good solutions. Genetic algorithms simulate the Darwin selection logic. Holland (1975) defines the evolutionary procedure as follows:

- Start with an initial population that is randomly generated, but containing the variability of parameter characteristics of the population;
- The fitness of each individual in population is accessed according to a fitness function;
- The probability of each individual to survive is proportional to its fitness;
- The individuals of next generation are selected based on probabilities and through a genetic transformation process of crossover and mutation, ensuring that the solution is not localized within the solution environment.

The formulation of genetic algorithm comprises four main elements; the encoding scheme, the genetic algorithms operators, the problem to be optimized and the objective function translated into the genetic algorithm as the fitness function. The encoding scheme involves the process where the genes of the algorithm are converted into input parameters of the process. An important component in the encoding process is to assure that the constraints and the parameters values are verified. Normally, a random process is used to generate the initial set of genes. Thereafter the genes are converted into parameter values and the feasibility of the solution is verified. If the solution is unfeasible, the process is repeated until a feasible solution is found. This is called the initial population. It should be pointed out that the selection of the initial population has to assure that the parameter values are uniformly distributed over the search space. The three operators in typical genetic algorithms are selection, crossover and mutation. Selection is the process used to select individual for reproduction to create the next generation. This process is made through a fitness function that makes higher fitness individual more likely to be selected for forming the next generation. After selection, the individual's chromosomes or parents are crossed randomly to produce their offspring's chromosome. Finally mutation consists in altering one or more genes in a chromosome from its initial state and is used to allow the algorithm to avoid local optimum by preventing the populations of chromosomes to be very similar to each other.

2.2.2 Tabu search

One of the fundamental capacities of heuristics it is their ability to avoid local optimums. Tabu search, Glover (1989) and Glover (1990), uses a short-term memory of recent solutions to escape entrapment in local optima of the solution space. This is achieved by a strategy that forbids certain moves. The purpose is to classify some moves as tabu with the aim of preventing circling between the same group of solutions. Tabu search also permits backtracking to previous solutions, which may ultimately lead to finding better solutions. The tabu process follows by recording moves in the order in with they are made. Each time an element is added to the bottom of the list, the oldest element that drops from the top is removed. The tabu list size is a very important parameter of the method and it should grow with the size of the problem. Other issues arise when the move found is tabu. Associated with each entry in the tabu list, there is a value for the evaluation function called aspiration level. This aspiration criterion is designed to override tabu status if a move is good enough. Cunha and Ribeiro (2004) propose a tabu search algorithm to find least cost designs of looped water distribution systems. According to this work, the correct fine-tuning of the parameters of the method permits to obtain high quality solutions for several benchmark problems in literature.

2.2.3 Ant colony

Dorigo *et al*. (2000) uses an evolutionary algorithm based on ant colony optimization method to the optimal design of water distribution systems. Ant colony algorithms are inspired by the fact that ants are able to find the shortest path between their nest and the food place, even being almost blind. This is made possible by using pheromone chemical tracks as a form of secondary communication. Ants deposit pheromone trails every time they travel. The route taken by individual ants from the nest in search for food is almost random. But when many ants are looking for food simultaneously, the paths are affected by the pheromone trails laid by other ants. When ants find pheromone trails, there is a high probability that trails with high pheromone concentrations will be chosen. As more ants travel on paths with high pheromone intensities, the pheromone on these paths increases more, making it even more likely to be chosen by other ants. From this consideration results that when an ant has to choose a path, it is likely to chose the path with high pheromone intensity. A parallelism can be made between this process and the search for the optimal design of water supply systems. The works of Dorigo *et al*. (2000) and Maier *et al*. (2003) present this method and conclude that ant colony can be an alternative to genetic algorithms.

2.2.4 Simulated annealing

Physically, annealing refers to the process of heating up a solid to a high temperature followed by decreasing of the temperature slowly. The notion of slow cooling is adapted in simulated annealing to a slow decrease in the probability of accepting worse solutions during the exploration of the solution space. The capacity to accept worse solutions is essential to allow the algorithm for a more widespread search for the global optimum. This method was independently presented by Kirkpatrick *et al*. (1983) and Černý (1985) and is used to solve difficult combinatorial optimization problems. The iterative process is an adaptation of a Monte Carlo method proposed by Metropolis *et al*. (1953) to define search paths.

Simulated annealing is used in this work as the optimization method. In the next chapter a more extensive overview of this algorithm is made as well as the particular considerations adopted for the optimal design of water distribution systems. This methods was used by Cunha and Sousa (1999, 2001). The results achieved in these works for different water networks prove the aptitude of the method in this field.

2.2.5 Hybrid heuristics

Determining the global optimal solution is computationally intractable for many combinatorial optimization problems, normally we are satisfied with “good solutions” which can be obtained by heuristic methods. One of the procedures to increase the performance of these methods is to join more than one heuristic, the so-called hybrid heuristics. These methods have been used with success in several areas. The work of Talbi (2002) categorizes the different hybrid heuristics with the objective of determining a common terminology and a global classification mechanism. A high percentage of hybridizing population based heuristics with local search heuristics has been proposed for various optimization problems. Pure based heuristics such as genetic algorithms are not well suited to fine-tuned search in highly combinatorial spaces.

Jeon and Kim (2004) present an algorithm to minimize the losses in an energy network through an adequate operation. This algorithm is build based on a heuristic that uses simulated annealing and tabu search, because according to the authors, these methods together improve the convergence properties and decrease the computational time. Also on energy networks, Mantawy *et al*. (1999) presents an hybrid algorithm to the selection of some possible energy sources, during a period of time and with the objective to minimize the total operation cost. This hybrid algorithm uses genetic algorithms, tabu search and simulated annealing. In the aquifers field, Shieh and Peralta (2005) present a hybrid model for the optimization of a bioremediation process. This algorithm was applied to a contaminated aquifer and uses simulated annealing and genetic algorithms. The authors determine that these heuristics found better results when used together compared with the results obtained when the heuristics were applied isolated.

Zhao and Zeng (2006) present a mathematical stochastic methodology for transit route network optimization. The objective is to provide an effective computational tool for the optimization of large-scale transit route directness while maximizing service coverage. The methodology includes representation of transit route network solution search spaces, representation of route and the stochastic search scheme based on an integrated simulated annealing and genetic algorithm solution search method. The methodology has been implemented as a computer program tested using previously published results and applied to a large scale realistic network optimization problem.

Mantawy *et al*. (1999) present an algorithm based on integrating genetic algorithms, tabu search and simulated annealing methods to solve the unit commitment problem. The core of the proposed algorithm is based on genetic algorithms. Tabu search is used to generate new population members in the reproduction phase of the genetic algorithm. The simulated annealing method is used to accelerate the convergence of the genetic algorithm by applying the simulated annealing test for all the population members. Numerical results showed the superiority of the obtained solutions compared to genetic algorithms, tabu search and simulated annealing methods and to two exact algorithms.

Baños *et al*. (2007) present a hybrid heuristic based on simulated annealing and tabu search to solve the "graph partitioning problem". This algorithm uses an external archive to memorize the best solutions found so far during the research process. As conclusions, the authors claim that the hybrid heuristic performs better than the heuristics separately applied. Following this work, Reca *et al*. (2007) applied hybrid heuristics in water supply systems and compared the performance of some heuristics in real networks. These authors found that for big networks, the hybrid heuristic that uses simulated annealing and tabu search was the one to found better results and decrease the computational calculus time.

Yoshikawa *et al*. (2008) discuss an optimal in situ bioremediation design by hybrid genetic algorithm and simulated annealing. The model uses a hybrid method for combining genetic algorithms and simulated annealing to search for an optimal design solution. This hybrid method is parallelized. Recombinative simulated annealing is a general purpose optimization approach that has a good convergence of simulated annealing and the efficient parallelization of genetic algorithm. Optimization results show that the parallel recombinative hybrid algorithms performs better than simulated annealing and genetic algorithms applied alone for optimizing system design when including installation costs.

Finally, Di pierro *et al*. (2009) represent a model to optimize water distribution and water quality in a regional water supply system. The optimization model is solved by a hybrid genetic algorithm. Genetic algorithms are first used to globally search for the directions of all undirected arcs. Then a generalized reduced gradient algorithm embedded in the genetic algorithms is used to optimize the objective function for fitness evaluation. The proposed methodology was tested and the results obtained indicate that the suggested hybrid meta-heuristic is a viable way of solving efficiently a large-scale network system.

The efficiency of heuristics can be effectively improved by using hybrid heuristics. As it was stated, simulated annealing is used in this work as the optimization tool. However, a tabu list incorporated in the simulated annealing was adopted to avoid the entrapment of the algorithm between cycles of the same solutions. This improvement of the algorithm is presented with more detail in the next chapter.

2.3 Robust optimization review

Robust optimization models have sparked great interest in the scientific community and there is plentiful literature reporting the strides made in recent decades. This is a fairly new branch of science and is still at research stage.

Greenberg (2008) defines robust optimization has a method that considers uncertainty and is similar to stochastic optimization since it also works with random variables. The difference between these methods is that stochastic optimization only considers parameters with well-established probability distributions, while robust models consider, in addition, parameters whose probability distribution cannot be determined.

2.3.1 Robust optimization general application

Robust models have been considered in various areas of application as they may generate safer and more resilient solutions. Mulvey *et al*. (1995) proposed the concept of robustness and presented a major synthesis of this approach, including a theoretical introduction and some applications. In the theoretical introduction the authors look at two kinds of decision variables:

- x - vector of the design decision variables whose optimum value is not conditioned by uncertain parameters;

- y - vector of control decision variables which are subject to adjustment, depending not only on the value of the uncertain parameters but also on the optimum value of the x variables.

Mulvey *et al*. (1995) consider a generic robust optimization model given by:

$$min \quad f(x,y_1,...,y_s) + C_{pen} \times p(e_1,...,e_s) \tag{2.1}$$

subject to:

$$Ax = b \tag{2.2}$$

$$H_s x + I_s y_s + e_s = j_s \qquad \forall s \in NS \tag{2.3}$$

$$x, y_s \geq 0 \quad \forall s \in NS \tag{2.4}$$

Where:

A,b - fixed value parameters;

H_s,I_s,j_s - uncertain value parameters of scenario s;

NS - number of scenarios;

e_s - error vector of scenario s that measure the infeasibility allowed by the control constraints (Eq. 2.3);

$f(x,y_1,\ldots,y_s)$ - function relating different decision variables;

C_{pen} - penalty coefficient used to find different solutions with differing robustness values and to compare them;

$p(e_1,\ldots,e_s)$ - penalty function used to penalize violations of the control constraints in some scenarios and to measure the model's robustness.

For the term $p(e_1,\ldots,e_s)$, and considering $prob_s$ the probability of occurrence of scenario s, the authors give two functions:

- $p(e_1,...,e_s) = \sum_{s \in NS} prob_s e_s^T e_s$ - a quadratic penalty function used on equality constraints when positive and negative constraint violations are considered;
- $p(e_1,...,e_s) = \sum_{s \in NS} prob_s max\{0,e_s\}$ - a penalty function applied to inequality constraints when only positive violations are of interest.

The term that calculates the robustness of the model $f(x,y_1,\ldots,y_s)$ used in the Eq. 2.1 can be given by different functions. Considering $\varepsilon_s = k^T x + d_s^T y_s$, in which k is a vector of fixed value parameters and d_s a vector of uncertain value parameters of scenario s, the authors give some possible functions:

$$f(x,y_1,...,y_s) = \sum_{s \in NS} prob_s \varepsilon_s \tag{2.5}$$

$$f(x,y_1,...,y_s) = \sum_{s \in NS} prob_s \varepsilon_s + C_{pen} \sum_{s \in NS} prob_s \left(\varepsilon_s - \sum_{s \in NS} prob_s \varepsilon_s \right)^2 \tag{2.6}$$

$$f(x,y_1,...,y_s) = - \sum_{s \in NS} prob_s U(\varepsilon_s) \tag{2.7}$$

Equation 2.5 is the objective function of the stochastic optimization models and should be used only in low risk situations. Equation 2.6 can be used for medium and high decision risk situations and is called a mean/variance model, in which the risk value is equated to the variance value so that the risk can be controlled via a penalty parameter *Cpen* in the penalty factor (2nd term of the objection function). The distribution of the variable ε_s needs to be symmetrical in relation to its mean value for this method to be used. Equation 2.7 can be used for high risk decision situations and it is based on the Von Neumann-Morgenstern utility curves in which, $U(\varepsilon_s)$ is a utility function. This method can be applied generally since it takes into account the probabilistic distributions of ε_s. Regarding the application of robust optimization the authors expose some cases of study. All these cases and the others to follow were numbered for the ease of systematization in the end of this literature review. The cases exposed by the authors are:

- Power capacity expansion problem (I);
- Matrix balancing problem (II);
- Image reconstruction (III);
- Airline allocation for the Air force: The STORM model (IV);
- Scenario immunization (V);
- Minimum weight structural design (VI).

Snyder (2006) also published an extensive literature review on infrastructure location problems solved using stochastic and robust optimization models. In the robust optimization models the author separates those composed of discrete parameters from others composed of continuous parameters, since the uncertainties of the discrete parameters should be held to vary within a pre-established range of possible values. In addition, the author describes two of the most common objectives used in these models, viz. the minimization of maximum costs and the minimization of maximum losses, in all possible accepted scenarios (MiniMax models).

Samsatli *et al*. (1998) published a work on robust optimization models applied to engineering systems. The authors described mathematical techniques capable of capturing different aspects of risk and some robustness measures are defined through modifications of parameters and functions. According to the authors, two approaches are widely used to formulate this model: probabilistic methodologies and methodologies based on scenario analysis. The latter is more usual. It requires the discretization of uncertain parameters to generate the scenarios and it gives a multi-scenario deterministic optimization problem. The scenarios can be determined explicitly if the combinations of parameters and associated probabilities are known *a priori*. On the other hand the scenarios may be generated implicitly assuming probability density functions for the parameters and using an approximation to express the integral. The authors define robustness in terms of the variance of a measure of performance or through combinations of the mean and the variance, and present some forms found in the literature. The authors however, do not believe that variance is a sufficiently general measure of robustness, and so they give a general measure of robustness based on the violation of a constraint. Based on that constraint, the authors show particular robustness measures, such as:

- Linear penalty functions;
- Taguchi quality loss function;
- Variance of constraints;
- Constraints of signal-to-noise ratio;
- Probability of constraint violation;
- Expected constraint violation.

To reduce the complexity of the problem only the uncertain parameters that have most influence on the process in terms of magnitude and response type should be included. Furthermore, the combinatorial nature of the problem can be reduced by approximating the binary variables by continuous variables. Two case studies were analyzed to apply these assumptions: the optimization of chemical reactors (VII) and the optimization of a fermentation process (VIII). As it was stated, all the cases were numbered for the ease of systematization in the final of the robust optimization literature review.

Suh and Lee (2001), too, proposed a robust optimization approach for the planning and design of chemical processes. The general formula of the robust model described is similar to the stochastic model, but it has one extra constraint (eq. 2.12):

$$Min \sum_{s=1}^{NS} prob_s Ct_s \tag{2.8}$$

subject to:

$$Ct_s = f(x, y_s, \theta_s) \qquad \forall s \in NS \tag{2.9}$$

$$h_s(x, y_s, \theta_s) = 0 \qquad \forall s \in NS \tag{2.10}$$

$$g_s(x, y_s, \theta_s) \leq 0 \qquad \forall s \in NS \tag{2.11}$$

$$R(Ct) \leq R_{lim} \tag{2.12}$$

Where:

$prob_s$ - probability of occurrence of scenario *s*;

Ct_s - costs in scenario *s* calculated from function $f(x, y_s, \theta_s)$;

x - design variables vector;

y_s - control variables vector for scenario *s*;

θ_s - uncertain parameters associated with scenario *s*;

$h_s(x, y_s, \theta_s)$ - vectors of equality constraints in scenario *s*;

$g_s(x, y_s, \theta_s)$ - vectors of inequality constraints in scenario *s*;

$R(Ct)$ - measure of robustness as a function of cost;

R_{lim} - limit value of robustness measure.

By excluding the constraint (2.12) we get a stochastic optimization model. If, instead of the objective function (2.8), the following is used:

$$\underset{x, y_s}{Min} \; R(Ct) \tag{2.13}$$

Then a pure model of robust optimization is achieved, that is called so because it is a model whose sole purpose is to minimize a measure of robustness. For different values of R_{lim} different cost solutions are obtained, and so a Pareto boundary can be constructed with pairs of optimal solution values. These solutions are given by resolving the stochastic model given by (2.8) to (2.11), which determines the top limit of the robustness measure $R(Ct)_{stochastic}$. Then the pure model of robust optimization is solved ((2.9) to (2.11) and (2.13)) to determine the lower limit of the robustness measure $R(Ct)_{robust}$. Once these limits have been found, the multi-objective problem is solved for values of R_{lim} in the range:

$$R(Ct)_{robust} \leq R_{lim} \leq R(Ct)_{stochastic} \tag{2.14}$$

Finally, a model for designing a biological reactor for a wastewater treatment plant (IX) proposed by Afonso and Cunha (2007), should be mentioned. In this model the robustness measure is given by the sum of the absolute value of the partial derivatives of performance in order of the parameters subject to uncertainty, so it is given as the sensitivity of the system to modifications of certain parameters.

2.3.2 Robust optimization applied to water supply systems

Babayan *et al*. (2005) solved the problem of the optimum robust design of water supply systems using two methods, one based on redundancy of the system (X) and another based on an integration method (XI). These authors consider the robustness of the system as the probability of simultaneously satisfying all the pressure constraints that is, guaranteeing nodal pressures above a pre-set figure, for all the system’s nodes. The sources of uncertainty considered in these methods were the nodal consumption and the coefficients of roughness of the pipes.

Cunha and Sousa (2010) presented a decision model for designing a WSS (XII) based on the concept of robust optimization and solved by means of a simulated annealing algorithm. Through this model the authors show, for a network subject to different consumption scenarios, the increased costs associated with gains in robustness for different values of a penalty coefficient, which makes it possible to give decision makers cost-robustness tradeoffs for choosing the decision to adopt.

For the robust management of water supply systems, Jeong *et al*. (2006) propose a mathematical model capable of identifying a WSS's vulnerabilities, the optimal allocation of available security resources and the reduction of the consequences of pre-planned terrorist attacks. The authors describe a model to control, or determine a suitable way to operate, a water supply system damaged by terrorist attack (XIII). Terrorist attacks may be chemical, biological, cyber or physical, but this article focuses on physical attacks because they are the most likely on account of the low level of expertise required to mount them. After an attack, just one part of the system is assumed to remain functional. The mitigation model developed by the authors allows the consequences of a cut to the water supply to be reduced by means of ascribing a priority level to each consumption node of the network.

Carr *et al*. (2005) report models used for the robust optimal placement of sensors in a WSS to detect contaminants accidentally or criminally injected into a particular network node (XIV). Here it is assumed that all the points downstream of the contaminated node are affected. The authors describe two kinds of decision models: the expected reduction of network contamination as defined by the number of contaminated nodes and the minimization of the number of people exposed to contamination.

2.3.3 Systematization

A detailed analysis of the mentioned works has made it possible to establish the following modes for including robustness in the specified optimization models:

- **Multi-scenario analyses** – the decision model is solved for a series of scenarios, that is, for different values of uncertain parameters, so that the global solution obtained functions properly for all the scenarios tested;
- **Parameter variance** – in the objective function of the model, a term is implemented to calculate the variance of a particular uncertain parameter;
- **Penalty factors** - constant parameters of the model normally used to penalize constraint violations, and, through their variation, to find different possible solutions with different robustness values;
- **Utility functions** – determine the benefits of a particular process according to the satisfaction of the objectives achieved;
- **Security factors** – the uncertain parameters of the model are increased so that the final solution will function well, even in adverse circumstances. The larger these factors the greater the robustness of the final solution and the higher the cost of the solution;
- **Integration method** – used to calculate the mean and standard deviation of the uncertain parameters so as to arrive at values that can be used as security factors in the control constraints;
- **Performance variation** – established by the derivative of a performance measure of the system in order of the different uncertain parameters of the model which conveys the sensitivity of the system to parameter modification; Limiting superiorly this derivative is to limit the variation of system performance and with this, impose a minimum level of robustness;

- **Constraint violations** – used to quantify the error in parameters determined by solving the model and the target values that should have been obtained; (in the case of water supply systems, a common constraint of this type is the violation of minimum admissible pressure at various nodes of the system);
- **MiniMax** – models which use objective functions that aim to reduce the maxima of certain parameters in all the possible scenarios so that the solution arrived at functions even in the worst possible situations.

A table has been constructed that summarizes the modes of including robustness in the optimization models presented in this review. The different robustness modes used can be checked quite quickly.

Table 2.1: Modes of including robustness in decision models

	Modes of Robustness Inclusion								
Models	**Multi-cenario Analysis**	**Parame-ters Variance**	**Penalty factors**	**Utility Fun-ctions**	**Security Factors**	**Integra-tion Methods**	**Perfor-mance variabi-lity**	**Cons-traints Violation**	**Mini-Max**
I	✓	✓	✓					✓	
II			✓					✓	
III			✓					✓	
IV	✓		✓	✓				✓	
V	✓	✓							
VI	✓								
VII	✓							✓	
VIII	✓							✓	
IX							✓		
X					✓				
XI			✓		✓	✓			
XII	✓	✓	✓					✓	
XIII			✓						
XIV	✓								✓

Table 2.1 presented a systematization of the different modes found in the case study literature on the inclusion of robustness in decision models. This literature review has enabled some conclusions to be drawn, as set forth below:

- A robust solution of a model is one which remains ‘close’ to the optimum for any values of uncertain parameters;
- Robust optimization can be applied to many areas of science to find more ‘secure’ solutions;
- When designing water supply systems, robust optimization methods lead to solutions that function satisfactorily, even under extreme operating conditions;
- The principal forms of including robustness in the optimization models found in the literature are multi-scenario analysis, penalty factors and constraint violations.

Based on this literature review, chapter 4 will present a robust optimization model. This part of the thesis presents a decision making process for the optimal design of water supply systems. The modes of including robustness on this work are the use of multi-scenario analyses, constraint violations and penalty factors.

2.4 Real options review

The concept of flexibility can be shown as a useful strategy to cost-effectively respond to uncertainties by considering them in advance. Water supply systems are operated under many uncertainties from water demand, pipe roughness and component failures, like pipe ruptures or energy shortages in pumping stations. These ideas give a different perspective to decision makers compared with a robust optimization approach, and aims to identify flexible water network designs.

Over the last few decades water supply systems have been built with the aim of satisfying the ever increasing needs for drinking water. The expansion of cities and population growth cause a fast rise in the demand for water. Several methods for effective planning in the area of water systems have appeared in the literature. However, it is difficult to predict the future and a flexible planning can be used to cope with future uncertainty. In this context an approach called **Real Options**, originally from financial theory that can make an important contribution. Myers (1977) was the first to introduce the term real options, soon after the works of Black and Scholes (1973) and Merton (1973) which propose a solution to the financial option valuing problem. Since then a large number of studies have been published where these concepts have been used in several fields. The real options concept is analogous to financial options, but the first refers to physical assets such as buildings and infrastructure, rather than financial instruments like stocks and shares, like the latter.

Wang *et al*. (2004) divide real options into two classes: real options “on” projects and real options “in” projects. Real options “on” projects are defined as pure financial options taken on technical elements, treating technology itself as a “black box”. The concerns in this case are related with evaluating the investment opportunities and determining the correct value to justify investment decisions. Some cases of real options “on” projects are the evaluations of new petroleum explorations, mineral explorations and in the pharmaceutical industry. By the other hand, real options “in” projects are options created by changing the actual design of the technical system and are focused on incorporating flexibility in the design. In this class of problems we have the evaluation of options for building extensions, bridge enlargements and water supply systems expansions.

Flexibility can be computed in several ways. De Neufville *et al.* (2006a) calculate it using the probability of maximum possible loss for real options valuation. Dixit and Pindyck (1994) use dynamic programing and Copeland and Antikarov (2001) use binomial decision trees. This flexibility has great importance in long planning horizon operation systems where uncertainty is high.

According to Dixit and Pindyck (1994) the value of flexibility is associated with three investment characteristics: irreversibility, uncertainty and option to delay decisions. The real options technique follows the same philosophy used to evaluate financial assets. Financial options give the right to buy or sell an asset, on a specific date and at specific price (exercise price). After the maturity date, the financial option expires and the obligation of the seller ends; the owner does not have to sell the asset for the agreed price.

The real options approach facilitates adaptive strategies as it enables the value of flexibility to be considered in the decision making process. Opportunities are provided for decision makers, to modify and update investments, when knowledge about future conditions is gained. This enables decision makers to identify the most appropriate long term intervention strategies. All the processes capable of changing the operating conditions over the time horizon, function of different possible scenarios, are processes where it is possible to use real options analysis. This concept gives some freedom to a decision strategy, because there is no need to take inflexible decisions and there is no specific date on which to take them. To summarize, real options implies the right but not the obligation to take some decision. It permits flexibility in management, to adapt decisions in response to changing investment conditions. According to Schwartz and Trigeorgis (2004) real options can be split into seven categories:

- **Option to defer** – gives decision maker the opportunity to delay an investment until future uncertainties are known;
- **Time to build options** – provides for a series of options that may be undertaken during the planning horizon periods;
- **Option to alter operating scale** - provides options to expand or reduce investment depending on the future uncertainty;
- **Option to abandon** - if it is better to permanently abandon the investment;
- **Options to switch -** if there is a dramatic change of the conditions;
- **Growth options** - when it is possible to increase investment in future opportunities;
- **Multiple interacting options** - when there are several options that can be combined.

A number of studies have developed real options approaches to solve a variety of problems. Roberts and Weitzman (1981) analyzed the nature of sequential funding criteria during a time horizon. In industry: McDonald and Siegel (1986), Fine and Freund (1990), Alvarez (1999) and Andreou (1990) used real options to evaluate industrial investments; Kulatilaka and Marks (1988) built a method to capture the value of flexibility through changing the operation of an industrial process, He and Pindyck (1992) solved investment decisions in industries with flexible production capacities and Triantis and Hodder (1990) evaluated the flexibility of fixed capacity equipment with a complex operation.

In petroleum exploration, Paddock *et al*. (1988) used real options to evaluate the investment in an offshore platform. In electric power systems: Tannous (1996) compared flexible and rigid electrical systems; Louberge *et al*. (2002) used real options analysis to explore the optimal decisions on the geological disposal of nuclear waste from nuclear power plants; Morck *et al*. (1989) used real options to evaluate the available forest resources and price volatility during an investment period; Brennan and Schwartz (1985) used real options theory to determine the viability of a mineral exploration due to price fluctuations of the ore extracted and Spinler and Huchzermeier (2006) determined an analytical solution to evaluate the real options of non-storable production goods like electricity.

Other uses of real options approaches include: Nembhard and Aktan (2010), who systemized applications of real options to design and develop engineering problems; Leviäkangas and Lähesmaa (2002), who considered methods to evaluate an intelligent transport system; De Neufville *et al*. (2006)b, reporting the use of real options in car parking problems; Dobes (2008), who identified how real options can be used in adaptations to climate change, giving examples involving the construction of airport runways and flood defenses, and Gersonius *et al*. (2010) applied real options analysis to the option planning process in urban drainage systems to incorporate flexibility to accommodate climate changes while reducing the future flood risk.

In the water industry, a real options technique appears in the work of Woodward *et al*. (2011) to define maritime costal defenses to reduce the risk of flooding. In the area of water systems expansion, Suttinon and Nasu (2010) present an real options based approach where the demand increases. Zhang and Babovic (2012) also use a real options approach to evaluate different water technologies into water supply systems under uncertainty.

In the optimal design of water distribution networks, Huang *et al*. (2010) describes the application of real options to design of water distribution networks. The used methodology presents a flexible design tool based on decision scenario trees that reflect uncertainty associated with future demand for water. The authors use a genetic algorithm optimization model to find a flexible design for a simple case study.

According to Wang *et al*. (2004), real options has two stages: option identification and option analysis. Options identification consists on trying to find all possible scenarios for the future planning horizon. The option analysis stage uses an optimization model to find good solutions for planning. This formulation enables decision makers to include more possible situations and develop explicit plans for the planning horizon.

In chapters 5 of the thesis an overview of the real options approach and how it can be used in water distribution systems is presented. This is followed by a case study to explain the method. In chapters 6 and 7 approaches based on real options are also presented with the aim to provide flexibility to water distribution systems design.

Chapter 3

Optimization Tools

The objective of this chapter is to exhibit the optimization tools. This section starts with an overview of the operational research field and then presents the simulated annealing heuristics. An overview of this method is made. Some rules and parameters are discussed for the two kinds of tools developed: the single objective and multi-objective simulated annealing optimization methods.

Keywords: simulated annealing; single objective optimization; multi-objective optimization

3.1 Introduction

During the last decades, operational research has been one of the most important investigation fields, and numerous works have been published, treating a large number of different problems. Operation research deals with the application of advanced analytical methods to help make better decisions. This is a group of techniques with the aim of helping decision makers on several fields as industry, economics and engineering. Depending on the problem to solve, operational research provides different approaches:

- **Linear programing**, the constraints and the objective function are given by linear equations. The variables are continuous and there are efficient methods to solve these problems and to find the global optimums;
- **Non-linear programing,** at least one of the constraints or the objective function is a non-linear equation. These problems are more difficult to solve in comparison with linear programing. However if it is a convex type problem, efficient techniques as the generalized reduced gradient method can be used to solve them;
- **Integer programing,** some variables can only be represented by integer values, also called discrete variables. These problems can be linear or non-linear. If they are linear, branch and bound methods can be used to solve them efficiently. If they are non-linear the problem becomes very difficult to solve and some heuristic methods come to light to speed up the process of optimization, even if not guaranteeing the global optimum.

For some real problems, it is imperative to find acceptable solutions in short periods of time. This is the case of the optimal operation of water distribution systems. In this work, simulated annealing heuristic will be used as the tool to solve the optimization models.

Simulate annealing is a general method for treating a broad class of large, multivariable optimization problems. A wide application of this method is found in the physical sciences and engineering. The simulated annealing algorithm was proposed by Kirkpatrick *et al*. (1983), and independently by Černý (1985). These works describe an analogy between the cooling of melted solid and the optimization of a complex mathematical model.

For a solid to be frozen into a perfect crystal, it must be annealed by first melting and then cooling very slowly. However, if the cooling process is very quick, a glass with many defects is formed and the structure becomes disordered. This process was the base of inspiration to solve difficult minimization problems.

Simulated annealing is established in the theory of Markov chains. A Markov chain is a mathematical system that goes through transitions from one state to another, between a certain numbers of possible states. It is a random process that normally does not memorize the sequence of movements in the solution space. The succeeding state is only dependent of the current state.

As it can be possible to understand in the next lines, a simulated annealing process accepts or rejects randomly generated moves on the basis of a probability related to a temperature parameter. It can accept moves which change the value of an objective function in the opposite direction to that of the desired optimization value. Thus, for a global minimization problem, a move that increases the value of the objective function, also called an uphill move, may be accepted according to a computed probability. In this way, simulated annealing is able to explore, in theory, the full solution space. This means that simulated annealing can escape from local optima of the solution space. Moreover, solutions achieved are in theory, independent of the starting point.

When applied to a cost minimization problem, moves are accepted every time a new solution is found with a smaller cost, and can be accepted or not according to some computed probabilities if the cost increases. Both capital and operating costs can be considered in the objective function and constraints can be easily implemented in the process. Any move which would violate a constraint can be rejected completely or accepted and penalized in the cost function. One of the greatest strengths of simulated annealing is the easy way with which discrete variables and discontinuous functions can be handled. These are the circumstances of the optimal design of water distribution systems. Simulated annealing is based on the Monte Carlo technique developed by Metropolis *et al*. (1953) to study the statistical mechanics of condensed systems (dense gases, liquids and solids). The Monte Carlo technique consists basically on computational algorithms that repeatedly generate random samples to obtain numerical results and to compute heuristically some probabilities. The technique is used by professionals in broadly different fields as engineering, research and development, energy, manufacturing, insurance, finance, project management, transportation and the environment. The mathematics underlying the Metropolis algorithm are given by Hammersley and Handscomb (1966) and Valleau and Whittington (1977) and are beyond the scope of this work.

Lundy and Mees (1986) and Romeo and Sangiovanni-Vincentelli (1984) establish that, if the number of attempted moves at each temperature is infinite, simulated annealing finds asymptotically the global optimum solution of combinatorial optimization problems with probability one. In practice, it cannot be guaranteed that the solution obtained by simulated annealing in a finite extent of time is the global optimum. However, results achieved on different problems suggest that a sufficiently slow annealing schedule will provide an optimal or near-optimal solution that is independent of the initial solution and, therefore, in principle avoids becoming trapped in local minima of the objective function that remains between the initial solution and the global optimum.

As it was stated in the last chapter, different heuristic methods with the aim of solving the problem of the optimal design of water distribution systems can be used.

However, this work adopts simulated annealing. This method has been used with success by the research group where this work was developed. Furthermore, simulated annealing is able to: deal with highly nonlinear models and with many constraints, escape from local optimums, find good solutions in short computational time, it can easily be adapted to water supply systems optimization, and be used with success in water infrastructures.

It is also important to highlight some difficulties to the use of simulated annealing. Since this is a meta-heuristic method, a lot of choices are required to turn it into a particular algorithm. Also, there is a clear tradeoff between the quality of the solutions and the time required to compute them. An initial work is necessary to account for different classes of constraints and to fine-tune parameters of the algorithm can be rather delicate. However, according to the work of Cunha and Sousa (1999) simulated annealing can be successfully used to solve these problems.

3.2 Analogy with the physical process

Most of the heuristics presented in chapter 2 are inspired in nature. There is the perception that if it is possible to replay mathematically what nature does, a powerful optimization method can be build. Natural processes are always quite efficient.

As it was stated, an analogy between the cooling of melted solid and the optimization of a complex system was made to conceive simulated annealing. This process requires that within the optimization context an analogy of the temperature of physical systems must be identified. The simulated annealing temperature is used to control the probability for accepting uphill moves. The temperature starts at high value so that a high proportion of attempted changes are accepted. As the simulation progresses, temperature is reduced periodically, according to an annealing schedule. In each reduction in temperature, the proportion of accepted moves goes down until, in limit, no uphill in cost moves are accepted. Providing that the annealing has been performed slowly enough, the final solution should represent the global minimum of the simulated annealing algorithm. Figure 3.1 represents the analogy between the physical annealing process and the optimization problem.

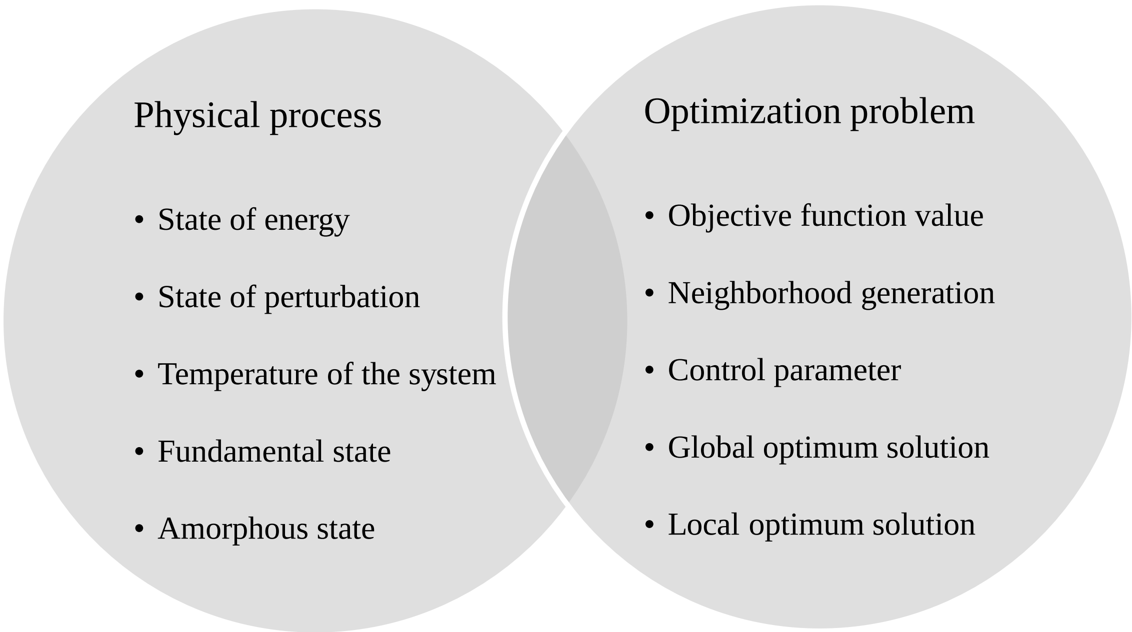

Figure 3.1: Analogy between the physical annealing and the optimization process

The analogy presented in Fig. 3.1 is made for minimization problems, but a generalization for maximization problems can be done by converting the maximization in a minimization problem by simply changing the signal of the objective function.

3.3 Simulated annealing algorithm

The implementation of the simulated annealing procedure used in this work to solve a single objective problem is described in the flow chart presented in Fig. 3.2:

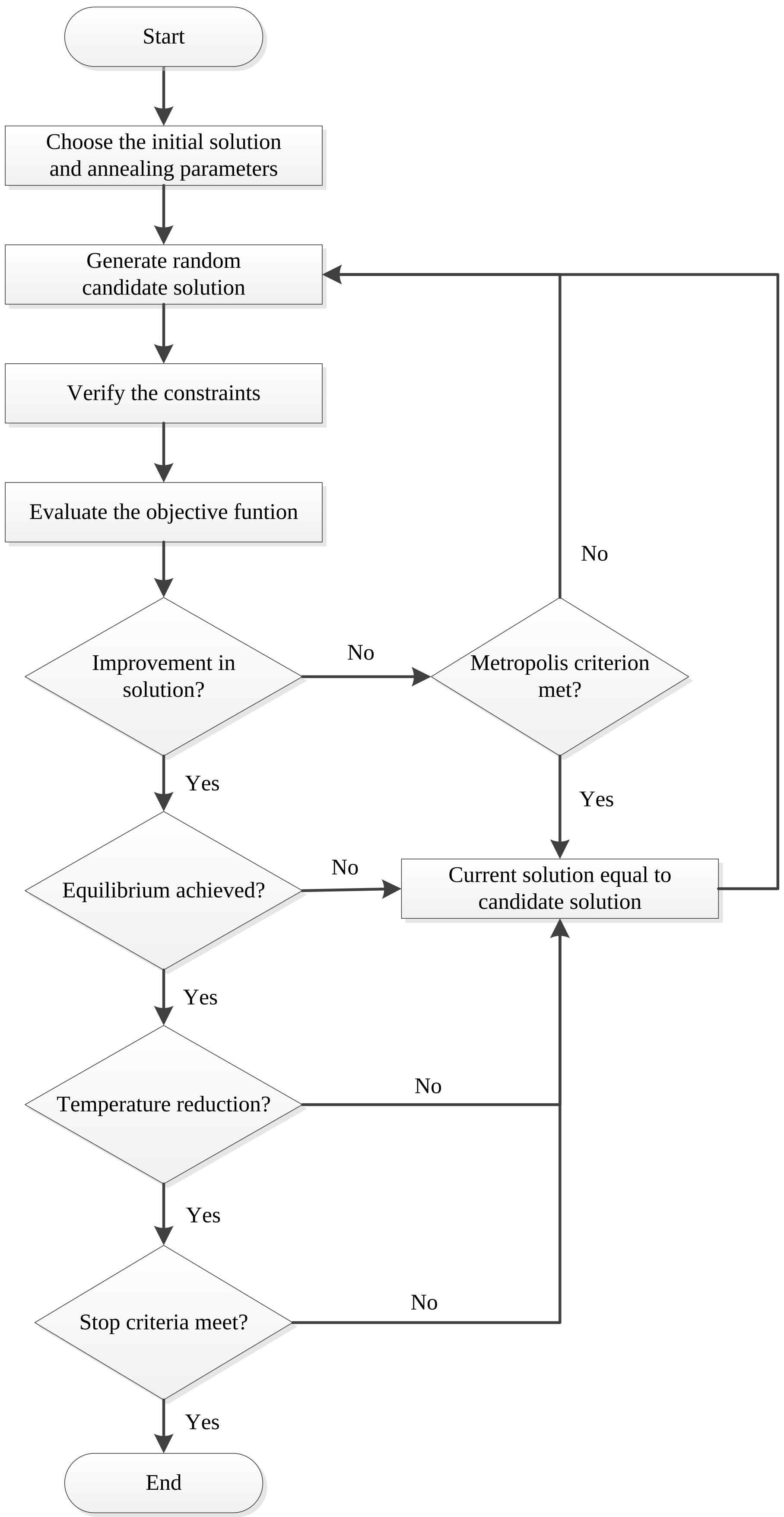

Figure 3.2: Simulated annealing flow chart

The simulated annealing process starts by choosing an initial solution generated randomly in the solution space. To it, is associated a value of the objective function. The current solution is initialized by considering it equal to initial solution. The candidate solution is selected in the neighborhood of the current solution and is given by a random change of current solution. After generation, the candidate solution can be accepted or not according to Metropolis criterion given by (3.1):

$$P_{acp} = \begin{cases} 1 \quad \text{if} \quad \Delta f \leq 0 \\ \exp\left(\dfrac{-\Delta f}{T}\right) \quad \text{if} \quad \Delta f > 0 \end{cases} \tag{3.1}$$

Where:

P_{acp} - probability of acceptance;

Δf - difference in value of the current and candidate solution;

T - temperature parameter.

If it is accepted, this solution will be used as the starting point for the next interaction. If not, the current solution will play this role. After a number of generations, the cooling process is performed and the temperature parameter decreases. The process progresses until some stop criterion is achieved. In the next lines the optimization tool used to solve single objective problems in water distribution network design is described more deeply. The algorithm implementation strategy is inspired on the works of Cunha and Sousa (1999) and of the Cunha and Sousa (2001).

3.3.1 Solution space

The group of possible solutions for a specific problem is so-called solution space. If the solution space is as small as possible then the search procedure is fast due to there are not many solutions to explore. It is intuitive that the number of interactions required converging to an optimal solution increase with the increase of size of the solution space. However if it is allowed to accept infeasible solutions, for example by accepting violations of constraints, this will increases the size of the solution space. The robust model presented in chapter 4 considers this possibility.

3.3.2 Selecting the initial solution

Every iterative technique requires the definition of an initial guess. Simulated annealing is a random search method that it is not very dependent from the initial solution choice. It is common to start with a random solution and let the annealing process improve on that. Some authors suggest that it should be chosen the worst solution of the solution space. In water distribution systems, this is made by giving the values for the decision variables that maximize the objective function. Normally this is traduced by giving the larger commercial diameters to pipes as well as the high possible size of singularities like tanks and pumping stations.

3.3.3 Building up the neighborhoods

The perturbation mechanism is the method to create new solutions from the current solution. It is the method to explore the neighborhood creating small changes in the current solution. The algorithm must provide a method for the current solution can be randomly changed to obtain a new one. From the theoretical prove of convergence of simulated annealing, every solution must be reachable from every other. Literature suggests different ways to build up neighborhoods. Furthermore, the neighborhood could be altered as the algorithm progresses by using an objective function with penalty terms that can limit the neighborhood according to the temperature parameter. The method used in this study to building up the neighborhood is based on the work of Cunha and Sousa (2001). According to the authors the network configuration should be randomly changed to obtain a new one. The method consist in first choose a pipe at random and then one choses a new diameter for this pipe. The new diameter will be randomly chosen, having a 40% probability of being the diameter one size above the actual size and 60% probability of being the diameter one size below the actual size. In the case of singularities pumps with fixed head or tanks, it is used the same probability to increase or decrease the physical characteristics.

3.3.4 Cooling schedule

Some authors argue that the cooling schedule is one of the most important aspects on simulated annealing algorithms because, from it, depends the computational time and the final solution quality. According to Cunha (1999) the cooling schedule consists of four components:

- initial temperature;
- cooling rate;
- number of iterations at each temperature;
- stop criterion.

In the following lines, it will be established the parameters to define the cooling schedule. There is a vast body of literature dealing with this problem. However these parameters are very dependent from the problem to solve. They should be defined through a sensitive analyzes of the performance of the algorithm for various combinations of parameters and considering different kinds of water networks. Cunha and Sousa (1999) made this analyzes and parameterization exposed here is based on this work.

3.3.4.1 Initial temperature

The initial temperature must be high enough to allow almost any move in the neighborhood. However if the temperature starts at too high value, the search can expend too much time in high temperatures, functioning like a completely random algorithm and not as a simulated annealing process. It can be found in literature empirical formulas to choose the value of the initial temperature. Some authors argue that the initial acceptance probability should be around 80%. The problem is to find the correct temperature to verify this percentage. There are some empirical expressions to define the initial temperature. The tools developed in this thesis follows the expression proposed by Cunha (1999) where the initial temperature is function of a parameter *EA* which can be termed as elasticity of acceptance. The initial temperature can be computed by Eq. 3.2:

$$T_{ini} = -\frac{0.1 \cdot C_{ini}}{\ln EA} \tag{3.2}$$

Where:

T_{ini} – initial temperature;

C_{ini} – cost of the initial solution;

EA – elasticity of acceptance.

Eq. 3.2 defines the temperature for the percentage of the solutions that should be accepted, whose cost increase is 10% the cost of the initial solution.

3.3.4.2 Cooling rate

Once the initial temperature is defined, it is necessary to decrement the temperature until arrives at the stopping criterion. The mode that the temperature is decremented is critical to the performance of the algorithm. Some authors state that it should be allowed enough iterations at each temperature so that a system stabilization can be achieved. However it should be noticed that the number of interaction at each temperature can be exponential to the size of the problem which is impracticable for real water distribution systems case studies. This means that if doing a large number of iterations, a few temperatures should be performed or in other way, a small number of interaction for a high number of temperatures.

One of the most used methods to decrement the temperature is the geometric decrement function given by Equation 3.3:

$$T_{t+1} = \alpha T_t \tag{3.3}$$

Where:

T_{t+1} – temperature for the next step;

T_t – temperature at the current step;

α – geometric annealing factor.

The geometric factor should assume values between 0.8 and 0.99. It should be pointed that the higher the value of α, the longer it will take to decrement the temperature until the stopping criterion is verified.

3.3.4.3 Number of iterations at each temperature

The number of evaluations to perform at each temperature is a parameter that depends from the dimension that is defined for the Markov chains, generated during the cooling process. This parameter can be one or infinite, according to the homogeneous and non-homogeneous algorithm (Hammersley and Handscomb 1966). In this work a minimum number of evaluations at each temperature is proposed, as a function of the number of variables of the problem to be solved. Simulated annealing algorithms should reach equilibrium at each temperature before progressing to a new temperature. This parameter will influence heavily the computational time. The developed optimization tool uses a method based on Cunha and Sousa (2001), aiming to increase the number of evaluations at each temperature, if a new optimum is reached. The application of this technic has the objective to intensify the search in more promising temperatures.

3.3.4.4 Stop criterion

Some authors defend that the temperature parameter should decrease until it reaches to zero. However, this can make the algorithm run much longer than when a typically geometric cooling scale is used. In this work a stop criterion given by two different conditions that need to be conjointly verified is adopted: the acceptance probability of new solutions lower than 5%, and two consecutive temperature decrements without an improvement of the optimum solution.

3.3.5 Improvements

There are also other important decisions that have to be made to build up the optimization tool. In the original simulated annealing algorithm, no memorization of optimal solutions during search is made, so that the method doesn’t use the information obtained during the search. This consideration has some risks because the theoretical prove of convergence of the method cannot be verified for the major of practical applications. So, it is highly probable that during the search, solutions better than the one found in the end of the process can be found. Therefore, an algorithm that keeps in memory the best solution found so far is used.

The empirical formula given by Eq. 3.2 is used to compute the initial temperature. However, when the acceptance probabilities determined by the initial temperature are smaller than 80%, a process to increase the initial temperature until this percentage is reached is performed, and after that, the cooling scheme can start. This can be seen has how physical annealing works, in the way that the material is heated until it becomes liquid, and only then the cooling begins.

Some authors have shown that hybrid heuristics can increase the quality of the solutions. When the search space is explored, simulated annealing search can cause the appearance of cycles and the algorithm becomes trapped under a constant change between the same solutions. A way to avoid this drawback is to use tabu lists, which contains the solutions visited in the previous interactions, in an attempt to avoid cycles in the search. Therefore, the adaptation of the tabu lists to the simulated annealing procedure is used. This combination of heuristics has been successfully applied to water supply systems. The results presented in the work of Reca *et al*. (2008) led to the conclusion that the use of tabu search in combination with simulated annealing improves the results obtained when only simulated annealing or tabu search are separately applied. According to this improvement, at each iteration, a solution is accepted only if the reverse movement is not stored in the tabu list. For example, if in an interaction a pipe diameter is changed from 500 mm to 400 mm, this solution is only accepted if in the tabu list there isn´t stored any movement of that pipe from diameter 400 mm to 500 mm. The tabu list size adopted in this work is equal to the number of decision variables of the problem. This list size proves to be adequate to the case studies analyzed in the research.

The optimization tool detailed in this sub-chapter 3.3 is used to solve the optimization models that will be presented in chapters 4, 5 and 6.

3.4 Simulated annealing for multi-objective problems

The tool presented in the next lines is used to solve the optimization model defined in chapter 7, and is mainly an adaptation of the single objective tool described in sub-chapter 3.3.

Multi-objective optimization problems are those problems for which there are two or more objectives of a system which need to be optimized. The solution of multi-objective problems aims to find decision variable vectors that simultaneously optimize the *n* objectives and obey to the constraints of the problem. An important concept of multi-objective optimization is dominance. With this concept it is possible to subdivide the solution space in dominated and non-dominated solutions. The multi-objective optimization can be represented by finding the vector v of Eq. 3.4 that optimize the values of the *n* objectives given by Eq. 3.5 and simultaneously satisfies the constraints of the problem.

$$v = \left[v_1, v_2, ..., v_n\right]^T \tag{3.4}$$

$$\left\{ f_1(v), f_2(v), ..., f_n(v) \right\} \tag{3.5}$$

To find a vector that optimizes the objectives, the multi-objective optimization uses the dominance concept. In minimization problems, solution v_i dominates v_j if conditions of Eq. 3.6 are verified.

$$\forall k \in 1, 2, ...n,\ f_k\left(v_i\right) \leq f_k\left(v_j\right) \text{ e } \exists k \in 1, 2, ...n: f_k\left(v_i\right) < f_k\left(v_j\right) \tag{3.6}$$

In other words, solution v_i dominates v_j if all the objective values determined by solution v_i are lower or equal to the objective values determined by solution v_j, and there at least one of the objectives on v_i is lower than the value of the objective determined in solution v_j. Single objective optimization models aim to find the global optimum that is unique in the solution space. But in multi-objective optimization case there are a groups of optimal solutions that normally are named “optimal Pareto front”, introduced by Pareto (1896). These are high quality solutions that cannot enhance more one objective without worsening the other.

3.4.1 Algorithm

This work presents an multi-objective simulated annealing algorithm inspired in the work of Bandyopadhyay *et al*. (2008). There have been only a few attempts in extending simulated annealing to multi-objective optimization problems, mainly because its sequential search nature. In the earlier attempts, a single objective function is built by combining the different objectives into one using a weighted sum approach. The problem here is how to choose the weights in advance and some alternative approaches have also been used in this regard. But this work uses a different approach that incorporates the concept of Pareto-dominance. The multi-objective simulated annealing also incorporates the concept of an archive where the non-dominated solutions seen so far are stored.

The structure of the proposed simulated annealing based multi-objective optimization tool is presented in fig 3.3. Some of the considerations made to build up the single objective tool are also valid for the multi-objective case. Building up the neighborhoods, the cooling process and the stop criterions are still valid in this method. But there are also some different procedures that will be set out in the next lines.

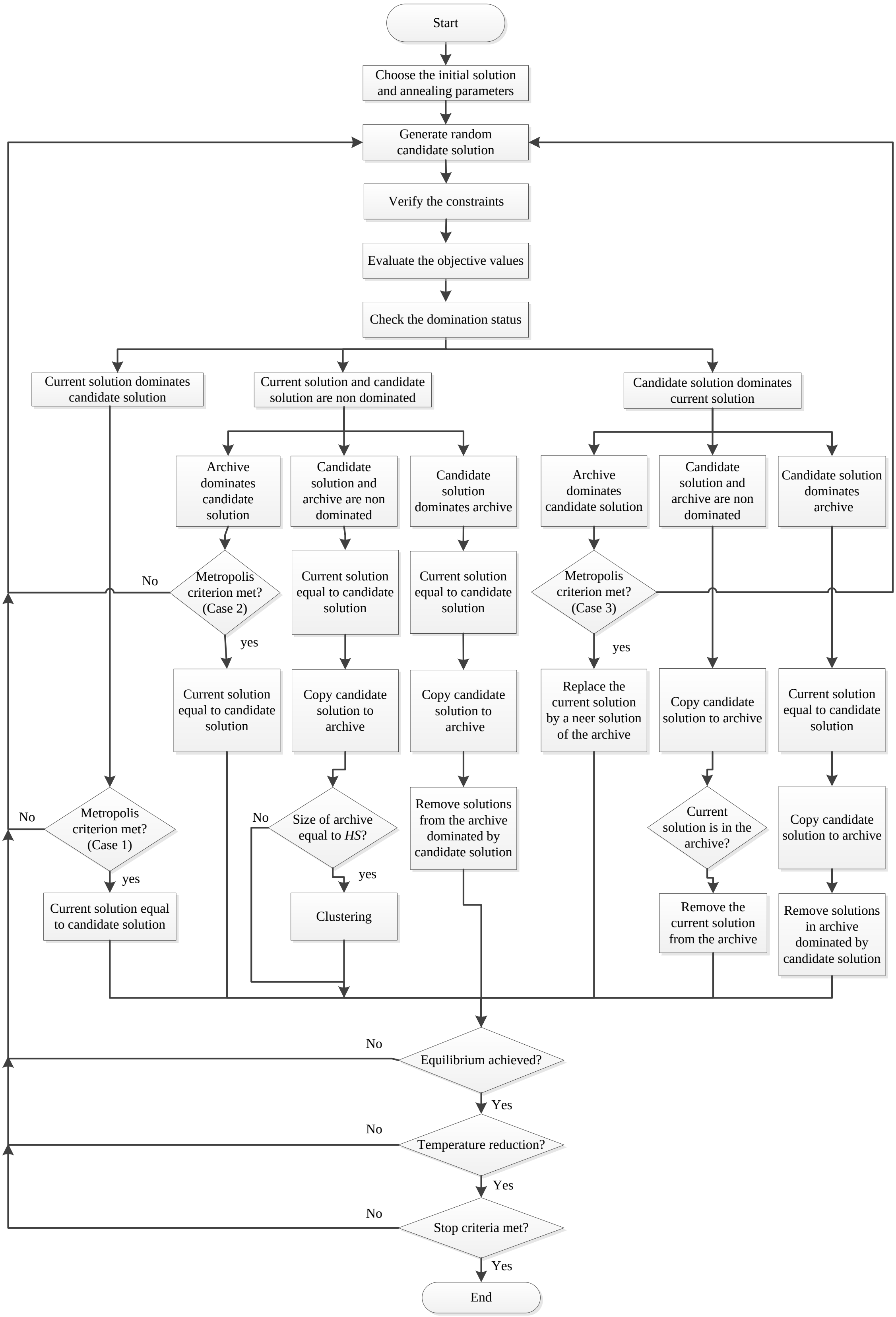

Figure 3.3: Multi-objective simulated annealing flow chart

This tool uses a memorization technique to save good solutions in an archive, since in the end a limited number of well distributed solutions are needed. The length of this archive is delimited in two levels. A lower limit, *LL*, and a superior limit, *SL*. During the search, the non-dominated solutions are saved in the archive until the number of solutions becomes equal to *SL*. After the archive reaches the maximum size, a clustering technique is used to reduce the size of the archive to *LL*. The clustering technique is based on the k-means methodology of Hartigan and Wong (1979). The consideration of two limits is made to reduce the number of times the cluster is called and to enable the formation of more spread out clusters.

3.4.2 Initial solution and initial temperature

To initialize the algorithm it is necessary to determine a group of non-dominated initial solutions. This step is made by a simple technique that generates solutions until a non-dominated solution is found. This solution is saved in the archive and the process continues until the total number of solutions saved is equal to *SL*. The first current solution is chosen randomly in the archive.

The multi-objective tool considers the initial temperature for simulated annealing determined by Eq. 3.13.

$$T_{ini} = -\frac{0.1 \cdot dom_{ini}}{\ln EA} \tag{3.13}$$

Where:

T_{ini} – initial temperature;

Dom_{inic} – initial dominance determined for the initial archive;

EA – elasticity of acceptance.

The initial temperature determined by this expression intends to obtain initial acceptance probabilities of 80%. If it obtains acceptance probabilities lower than this value, the initial temperature is incremented until this criterion is verified. Then the temperature decreases according to a geometric law.

3.4.3 Acceptance probability

The acceptance probability is distinct for the three different cases of dominance presented in Fig. 3.3. The dominance between two solutions is computed by Eq. 3.7:

$$\Delta dom_{a,b} = \prod_{i=1,\, f_i(a) \neq f_i(b)}^{N} \left| f_i(a) - f_i(b) \right| \tag{3.7}$$

Where:

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

N – Total number of objectives;

$f_i(a)$ – Value of objective i for solution a;

$f_i(b)$ – Value of objective i for solution b.

For case 1 of Fig. 3.3, the candidate solution is dominated by the current solution and the mean dominance is computed by Eq. 3.8.

$$\Delta dom_{mean} = \frac{\left(\sum_{i=1}^{p} \Delta dom_{i,cand} \right) + \Delta dom_{curr,cand}}{p+1} \tag{3.8}$$

Where:

Δdom_{mean} – mean dominance relatively to candidate solution;

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

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

p – Total number of solutions in the archive that dominates candidate solution.

This expression considers the sum of domination of all the solutions in the archive that dominates the candidate solution. This sum is divided by the number of solutions in the archive that dominates the candidate solution plus one to take into account the dominance of the current solution relatively to the candidate solution.

For case 2 of Fig. 3.3, the current and candidate solutions are non-dominated and the mean dominance is computed by Eq. 3.9:

$$\Delta dom_{mean} = \frac{\left(\sum_{i=1}^{p} \Delta dom_{i,cand} \right)}{p} \tag{3.9}$$

This expression is similar to case 1, however in this case, the dominance between the current and candidate solutions is not computed.

Lastly, case 3 of Fig. 3.3, the candidate solution dominates the current solution and the minimum dominance is computed, Eq. 3.10, as equal to the minimum value of dominance between the solutions of the archive that dominates the candidate solution.

$$\Delta dom_{\min} = Min(\Delta dom_{i,cand}, i = 1, \ldots p) \tag{3.10}$$

Where:

Δdom_{min} – Minimum dominance relatively to candidate solution.

After calculating the domination value, considering three different cases, the Metropolis criterion is used to compute the acceptance probability of the candidate solution. For cases 1 and 2 the acceptance probability is computed by Eq. 3.11, and for case 3 the acceptance probability is computed by Eq. 3.12.

$$P_{acp} = \exp\left(\frac{-\Delta dom_{mean}}{T}\right) \tag{3.11}$$

$$P_{acp} = \exp\left(\frac{-\Delta dom_{\min}}{T}\right) \tag{3.12}$$

Where:

P_{acp} – probability of acceptance;

T – temperature parameter.

According to the structure of the algorithm of Fig. 3.3, the multi-objective process is repeated for a number of iterations at each temperature. The temperature is reduced until the stop criterions are attained and the process stops. In the end of the process, the archive contains the non-dominated solutions.

In chapter 7 of the thesis, this tool is used in the optimal design of water supply systems considering conflicting objectives.

Chapter 4

Robust Optimization Methodologies for Water Supply Systems Design

This chapter presents a robust optimization model for the optimal design of water supply systems operating under different circumstances. The model presented here uses a hydraulic simulator linked to an optimizer based on a simulated annealing heuristic. The results show that robustness can be included in several ways for varying levels of reliability and that it leads to more reliable designs for only small cost increases.

Keywords: robust optimization; reliability; scenarios

4.1 Introduction

Modern societies are sustained by a number of vital networks. Energy, telecommunications, transport, water and sanitary infrastructures are responsible for a good life quality. A disruption in the water supply can cause enormous trouble, which means that the systems have to be designed to deliver a constant supply of clean, safe drinking water, even in adverse circumstances. Every water supply systems will certainly have to contend with some burst pipes and abnormal demands, such as from firefighting. These events can have a minor or major impact on the operation of the water supply systems and it is very important to maintain the supply and quality of water. According to DIEDE and AIDIS (2008), studies of hundreds of disasters worldwide clearly indicate that the continuity of drinking water and sanitation services is critical in post-disaster conditions, since they are essential to rapid social and productive recovery. Water can still be provided, even in adverse situations, if a proactive attitude is taken towards risk from the design phase until the end of the system's life span. However, it must be pointed out that if all the possible threats and vulnerabilities could be taken into account the cost would be prohibitive. Hence, decision makers must establish how much they are willing to pay to reduce risk. As a water supply system is a costly infrastructure its design and operation should be supported by optimization tools. Stochastic optimization and robust optimization (RO) appear to be promising techniques to solve these problems: the review by Mulvey *et al*. (1995) examines this area and describes some practical applications. RO has already been applied to water supply systems: Babayan *et al*. (2007), Jeong *et al*. (2006), Cunha and Sousa (2010), Carr *et al*. (2005) and Giustolisi *et al*. (2009) present a number of robust optimization models.

The model proposed by Cunha and Sousa (2010) for the robust design of water distribution networks includes multiple scenarios in the optimization model. These scenarios include the traditional peak discharge design and some abnormal working conditions like firefighting flows and pipe breaks. This approach also considers two levels of pressure: the desired pressure (minimum pressure to meet water demand) and the admissible pressure (minimum pressure allowed for the abnormal conditions scenarios). The pressure for the peak discharge design scenario is always higher than the desired pressure and so the network must be designed to meet the water demand under normal working conditions. The pressure for the abnormal scenarios is allowed to take lower values, although they are always higher than the admissible pressure. However, if the pressure is lower than the desired pressure then part of the water demand will not be met and the objective function is penalized.

The solutions obtained with this method showed that a robust design, a design that will meet all the desired pressure requirements even under abnormal working conditions, can be considerably more expensive than the traditional design solution (peak discharge design). As the case study used in Cunha and Sousa (2010) was a gravity fed water distribution network, the pipe diameters had to be increased to meet the pressure conditions in all scenarios, and consequently this added to the cost. For example, if the water demand is to be fully met during a pipe bursts the flow needs alternative paths to reach the demand nodes downstream of the break, and those paths must have enough capacity to carry a discharge that is higher than usual. As the pipe cost increases significantly with the diameter, this additional capacity is quite expensive. It must also be pointed out that larger diameters lead to low velocities and high water residence times, neither of which are desirable in terms of water quality and safety.

This work proposes a different approach. As larger pipe diameters significantly increase the cost and lead to low velocities, it might be possible to cope with abnormal working conditions, which occur sporadically and last a short time, by adding a pumping station to be used like a contingency infrastructure. The strategy of this work involves a gravity fed network design to cater at least for normal working conditions (peak design flow) and a pumping station to add energy to cope with abnormal working conditions. The pumping station will only be planned to operate under abnormal working conditions, so the energy consumption can be neglected. It was also considered that the pressure under abnormal working conditions could be higher than under normal working conditions, but never above a maximum pressure constraint introduced in the optimization model. This will limit the elevation of the pumping station in abnormal conditions only to safe levels of operation.

With this contingency infrastructure, the network does not need to be overdesigned to attain the desired robustness, and this reduces the complications that can arise from low velocity problems. It can also be seen as another way to increase robustness in an existing water supply system, where solutions such as increasing the pipe diameters may be hard to implement in an urban environment.

The optimization model is presented next, in section 4.2, then the model is tested on 2 case studies in section 4.3, and the results and comparisons are presented in section 4.4. Finally, the conclusions are set out in section 4.5.

4.2 Robust model

The model proposed herein is based on the work by Cunha and Sousa (2010) and is used for the robust design of water supply systems when exposed to different operating scenarios. In this proposed model a new approach for achieving the desired robustness is considered, specifically, one which uses a pumping station instead of increasing the pipe diameters. The goal of the model is to find designs that will perform well even under abnormal conditions (pipe breaks or firefighting). The optimization model is solved by the simulated annealing algorithm proposed in Aarts and Korst (1989), used by Cunha and Sousa (1999) and Cunha and Sousa (2001) and adapted for this work. The model is linked to a hydraulic simulator that verifies the hydraulic constraints. A hydraulic simulator based on a pressure driven approach is used to verify the hydraulic constraints. Considering the sum of probabilities of all the scenarios to be equal to 1, the objective function is formulated in Eq. 4.1:

$$\begin{aligned} Min \ & \sum_{i=1}^{NPI} Cpipe_i(D_i)L_i + \sum_{j=1}^{NPU}\left(CCps_j + CEps_j\right) + \\ & + \sum_{s=1}^{NS} prob_s \left[\begin{aligned} & Cpenp \cdot \sum_{n=1}^{NN} \max\left\{0;\left(PMINdes_s - P_{n,s}\right)\right\}^2 + \\ & + Cpend \cdot \sum_{n=1}^{NN} \max\left\{0;\left(QD_{n,s} - QC_{n,s}\right)\right\}^2 \end{aligned} \right] \end{aligned} \tag{4.1}$$

Where:

NPI - number of pipes in the network;

$Cpipe_i(D_i)$ - unit cost of pipe i as a function of its diameter D_i;

D_i - diameter of pipe i;

L_i - length of pipe i;

NPU - number of pumping stations in the network;

$CCps_j$ - construction cost of the pumping station (PS) j in €;

$CEps_j$ - equipment cost of the pumping station (PS) j in €;

NS - number of scenarios;

$prob_s$ - probability of scenario s;

$Cpenp$ - penalty coefficient for minimum pressure violations;

NN - number of nodes;

$PMINdes_s$ - minimum desired pressure for scenario s;

$P_{n,s}$ - pressure at node n for scenario s;

$Cpend$ - penalty coefficient for demand violations;

$QD_{n,s}$ - demand at node n for scenario s;

$QC_{n,s}$ - consumption at node n for scenario s.

The construction cost and the equipment cost of the pumping station is given by:

$$CCps_j = 39904 + 374 \times Qps_j + 0.15 \times Qps_j \times Hps_j \quad \forall j \in NPU \tag{4.2}$$

$$CEps_j = 1317 \times Qps_j^{0.769} \times Hps_j^{0.184} + 2092 \times (Qps_j \times Hps_j)^{0.466} \quad \forall j \in NPU \tag{4.3}$$

Where:

Qps_j - highest pump discharge (l/s) for all the scenarios in PS *j*;

Hps_j - pumping head (m) for the highest discharge in PS *j*.

The objective function Eq. (4.1) includes the following costs: cost of the pipes and cost of the pumping stations (construction and equipment). But it also includes a penalty function for those solutions that do not meet the minimum desired pressure and demands: the sum of the quadratic violations of pressures and demands multiplied by penalty coefficients and weighted by the probability of occurrence of each scenario. The model includes a different set of constraints.

$$\sum_{i=1}^{NPI} I_{n,i} Q_{i,s} = QC_{n,s} \quad \forall n \in NN; \forall s \in NS \tag{4.4}$$

$$\Delta H_{i,s} = K_i Q_{i,s}{}^{\alpha} \quad \forall i \in NPI; \forall s \in NS \tag{4.5}$$

$$PMAX_{n,s} \geq P_{n,s} \geq PMINadm_{n,s} \quad \forall n \in NN; \forall s \in NS \tag{4.6}$$

$$D_i \geq D\min_i \quad \forall i \in NPI \tag{4.7}$$

Where:

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

$Q_{i,s}$ - flow in pipe *i* for scenario *s*;

$\Delta H_{i,s}$ - head loss in pipe *i* for scenario *s*;

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

$PMAX_{n,s}$ - maximum pressure at node *n* for scenario s;

$PMINadm_{n,s}$ - minimum admissible pressure at node *n* for scenario *s*;

$Dmin_i$ - minimum diameter for pipe *i*.

Eq. (4.4) is used to verify the nodal continuity equations; Eq. (4.5) is used to compute the head loss of the pipes; Eq. (4.6) is used to limit the pressure of the nodes and Eq. (4.7) is used to guarantee a minimum diameter for the pipes.

Furthermore, the optimization model uses a candidate diameter for each pipe based on a set of commercial diameters, given by Eq. (4.8) and guarantees the assignment of only one commercial diameter for each pipe through Eq. (4.9).

$$D_i = \sum_{d=1}^{ND} YD_{d,i}.Dcom_{d,i} \quad \forall i \in NPI \tag{4.8}$$

$$\sum_{d=1}^{ND} YD_{d,i} = 1 \quad \forall i \in NPI \tag{4.9}$$

Where:

ND - number of commercial diameters;

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

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

Two kinds of minimum pressure were considered in the model: the desired pressure and the admissible pressure. The pressure can be lower than the desired pressure but not lower than the admissible pressure. If the nodal pressure values remain between these two limits the objective function is penalized. In addition, if the pressure is lower than the desired pressure the nodal demands will not be totally satisfied and the objective function is penalized as a function of the difference between the actual water demand and the demand that is satisfied, Cunha and Sousa (2010). For pressure equal to or higher than the desired pressure the demand is totally satisfied and for pressures lower than the admissible pressure there is no nodal consumption.

4.3 Case studies

The model is applied to two similar case studies based on the network in Xu and Goulter (1999). In case study 1 (CS1), Figure 4.1, the network is gravity fed by a single reservoir with a fixed level of 55m and comprises 33 pipes and 16 nodes. Case study 2 (CS2), Figure 4.1, is similar but it introduces a PS downstream of the reservoir (link 34). This PS is a contingency structure that should be used only in abnormal working conditions. As these situations are usually short-lived, the energy consumption and its cost were neglected.

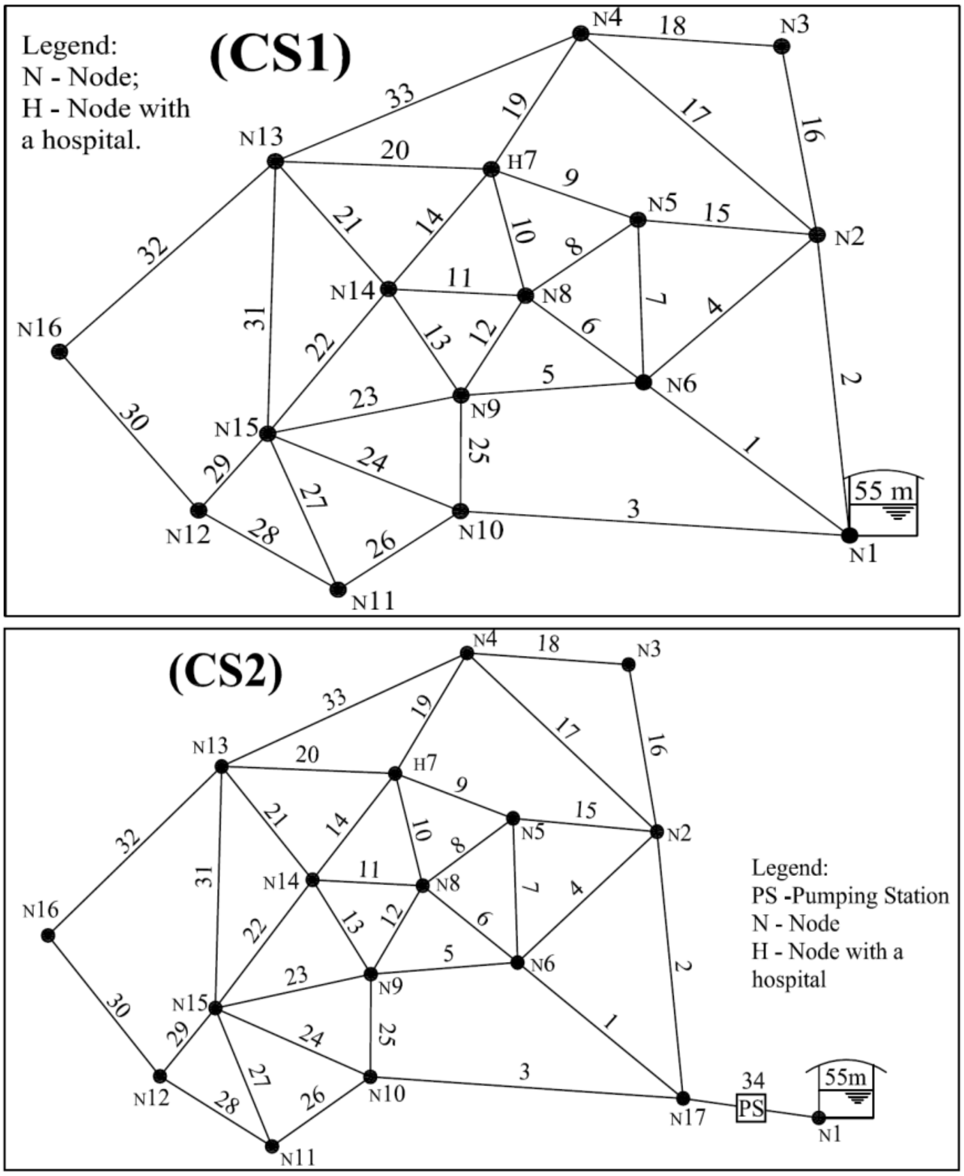

Figure 4.1: Network schemes: case study 1 (CS1) and case study 2 (CS2)

The characteristics of the pipes are given in Table 1 and the characteristics of the nodes in Table 2. The commercial diameters (and their cost) used in the present study are given in Table 3. The head losses were calculated using the Hazen-Williams equation. It is also assumed that there is a hospital in node 7 with special pressure and demand requirements.

Table 4.1: Characteristics of the pipes

Pipe	Initial node	Final node	Length (m)	Pipe	Initial node	Final node	Length (m)
1	1	6	3660	18	3	4	1830
2	1	2	3660	19	7	4	1830
3	1	10	3660	20	7	13	1830
4	6	2	2740	21	14	13	1830
5	6	9	1830	22	14	15	1830
6	6	8	1830	23	9	15	1830
7	6	5	1830	24	10	15	1830
8	5	8	1830	25	9	10	1830
9	5	7	1830	26	10	11	1830
10	8	7	1830	27	11	15	2740
11	8	14	1830	28	11	12	1830
12	8	9	1830	29	12	15	1830
13	9	14	1830	30	12	16	1830
14	14	7	1830	31	15	13	1830
15	2	5	1830	32	16	13	3660
16	2	3	1830	33	13	4	3660
17	2	4	2740	34	1	17	Pump

Table 4.2: Characteristics of the nodes

Node	Ground Elevation (m)	Peak Discharge (l/s)	Node	Ground Elevation (m)	Peak Discharge (l/s)
1	0	0	10	0	43.889
2	0	43.889	11	0	43.889
3	0	43.889	12	0	43.889
4	0	43.889	13	0	43.889
5	0	43.889	14	0	43.889
6	0	43.889	15	0	43.889
7	0	43.889	16	0	43.889
8	0	43.889	17	0	0
9	0	43.889			

Table 4.3: Commercial diameters, unit cost and Hazen-Williams coefficients

Diameters (mm)	Unit cost (€/m)	H-W coefficients	Diameters (mm)	Unit cost (€/m)	H-W coefficients
100	87	120	450	247	120
125	97	120	500	277	120
150	102	120	600	371	120
200	120	120	700	465	120
250	147	120	800	559	120
300	157	120	900	653	120
350	187	120	1000	747	120
400	215	120			

A multiple scenario approach was used to design the network for the two case studies:

- Scenario 1: Instantaneous peak discharge (IPD);
- Scenario 2: IPD and pipe 1 out of service;
- Scenario 3: IPD and pipe 2 out of service;
- Scenario 4: IPD and pipe 3 out of service;
- Scenario 5: IPD and a fire at node 3 (200 l/s);
- Scenario 6: IPD and a fire at node 12 (200 l/s);
- Scenario 7: IPD and a fire at node 13 (200 l/s).

The IPD is 1.8 times the average discharge. For case study 2, the maximum nodal pressures should not exceed 60 m for scenario 1 and should not exceed 90 m for scenarios 2 to 7, for the nodes of the network (N2 to N16). In the pipe break scenarios (2 to 4), it is assumed that the pipe that breaks can be isolated without compromising the supply of the respective end nodes. For scenario 1, the minimum desired and admissible pressures are 30 m for all nodes; for scenarios 2 to 7 the minimum desired pressure is 25 m and the minimum admissible pressure is 10 m for all nodes except node 7; as node 7 supplies a hospital, for scenarios 2 to 7 the minimum desired pressure is 30 m and the minimum admissible pressure is 25 m. In scenarios 5 to 7 it is assumed that the firefighting demands are completely satisfied even if the fire node pressure is lower than the desired pressure.

4.4 Results and comparisons

This work proposes a different approach to reinforce a water supply system so that it can cope with normal and abnormal situations, and then compares it with another possible solution. In both case studies the network must work under 7 different operating scenarios (the traditional peak design flow and 6 extreme scenarios - 3 burst pipe scenarios and 3 firefighting scenarios). The objective function of the robust optimization model includes pipe costs, pumping station costs (construction and equipment) and penalties for pressure and demand violations. Network robustness can only be achieved in case study 1 by increments in pipe diameters. The flow must have alternative paths with enough capacity to carry bigger discharges to overcome the extreme scenarios. Network robustness can also be achieved in case study 2 by using the pumping station to increase the head at the reservoir. For the extreme scenarios, which occur occasionally and only for short periods of time, it was assumed that the maximum nodal pressure should not exceed 90 m (this constraint limits the pumping head and avoids potentially excessive pressure in the network). This approach avoids the large pipe diameter increase imposed by the case study 1 conditions (gravity fed network).

The decision variables of the robust optimization model are: case study 1 – pipe diameters; case study 2 – pipe diameters and pumping head for scenarios (2 to 7) of fixed velocity pumps. The peak discharge design (PDD) is determined by solving the model considering only scenario 1. This design is used to compare the cost differences that the robustness solutions imply. To synthesize the results, only the PDD solution, the low robustness design (LRD) and the high robustness design (HRD) for each of the two case studies are presented. However, intermediate robust solutions can be achieved by considering different levels of robustness for the network, Cunha and Sousa (2010). The LRD assumes a low probability of occurrence of the extreme scenarios and includes small penalty coefficients. The HRD is obtained assuming a high probability of occurrence of the extreme scenarios and large penalty coefficients. Figures 4.2 and. 4.3 show the details of the solutions found for case studies 1 and 2. These figures show the commercial diameter chosen for each pipe in millimetres, the PS head in meters for the different considered scenarios, the partial and total cost of the solutions and also the total pressure and demand violations.

The “Total pressure violations” given in figures 4.2 and 4.3 represent the sum of all the pressure violations at all the network nodes and for all the scenarios. A similar procedure was used to compute the “Total demand violations”.

The figures show that pressure and demand violations are reduced by enlarging some pipes and the pumping heads, meaning that more reliable solutions imply higher costs. The presented HRD illustrates that the robust design enlarges the pipe diameters by creating “main rings”, which provide extra redundancies to supply all the nodes - even for the extreme considered scenarios. It should also be pointed out that those “main rings” always embrace the critical node – Hospital (H7). As expected, the solutions for case study 1 comprise the use of larger pipe diameters than for case study 2. In fact, the PS plays an important role in ensuring the network supply for case study 2; instead of using larger pipe diameters, reliability is achieved by the PS increasing the head at the reservoir for the extreme scenarios.

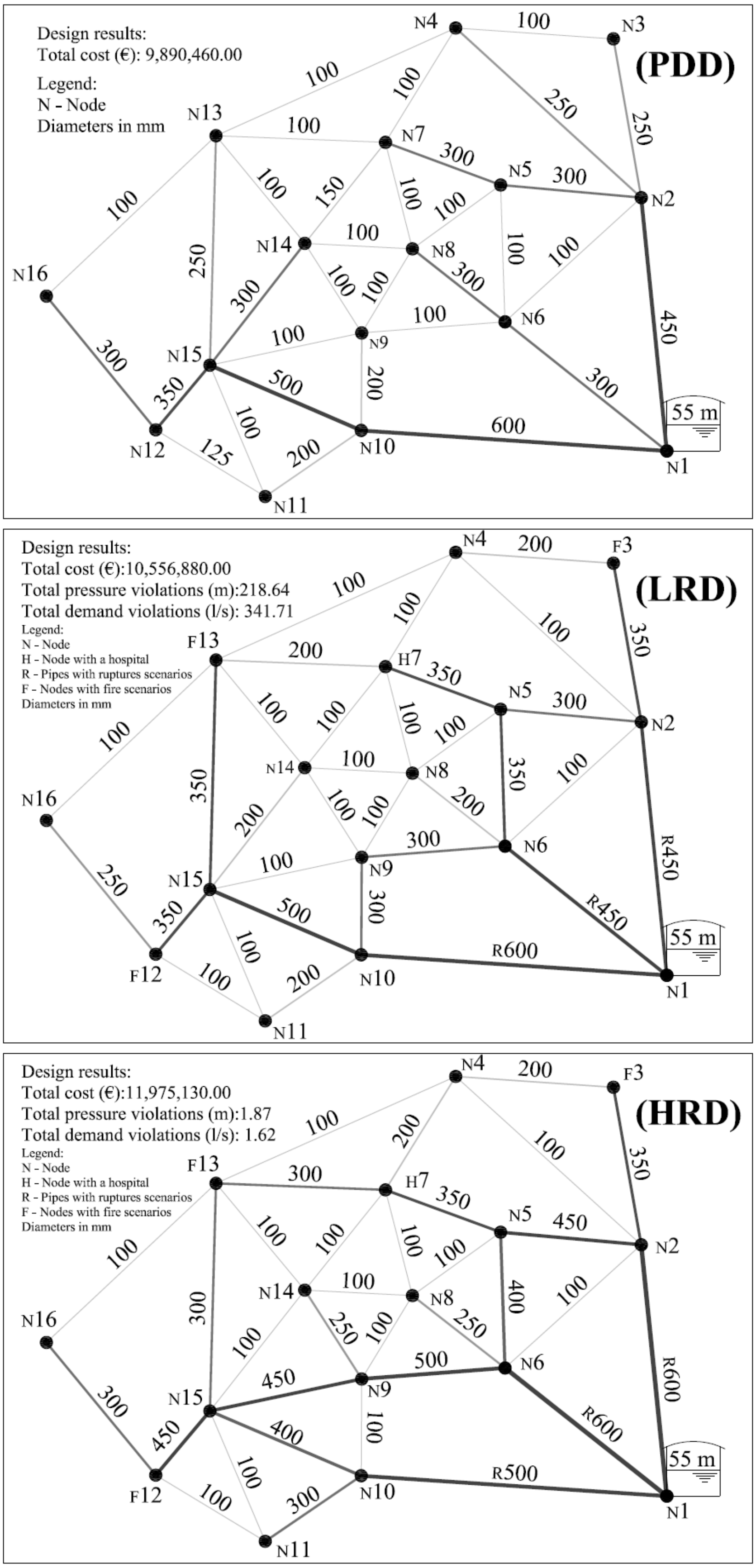

Figure 4.2: Designs for case study 1: (PDD) peak discharge (LRD) low robustness and (HRD) high robustness

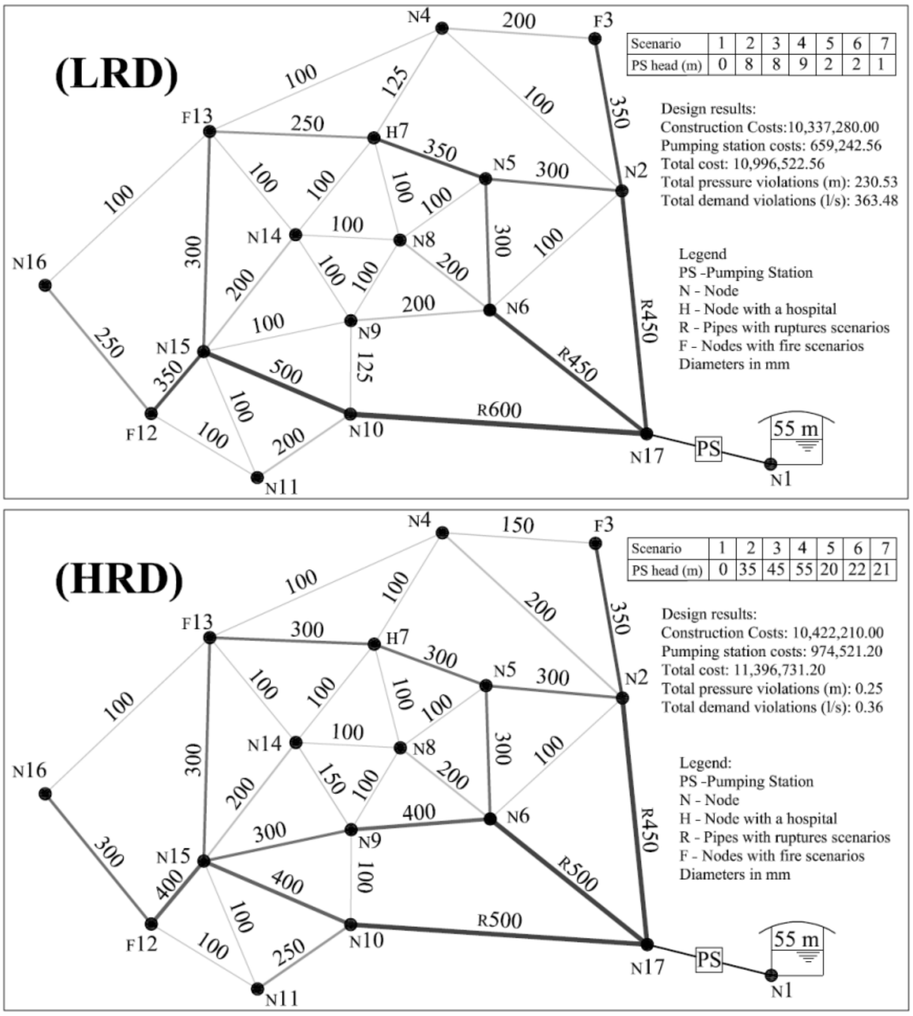

Figure 4.3: Designs for case study 2: (LRD) low robustness and (HRD) high robustness

Table 4.4 shows a comparison of the solutions obtained for the case studies (cost, pressure violations and demand violations, for the designs presented in figures 4.2 and 4.3). The increases in total costs for the LRD and the HRD are calculated taking the PDD cost as reference. The penalty coefficients for the two case studies were fixed so as to obtain solutions with similar pressure and demand violations for both case studies.

Some conclusions can be drawn from Table 4.4. In case study 1, the LRD costs are 7% higher, but to get a HRD would require spending 21% more than the cost of the traditional PDD solution. As robustness is achieved solely by enlarging the pipe diameters, the HRD for case study 1 has the highest total cost for the pipes - 11.975×10^6€ (this is the design with largest pipe diameters).

Table 4.4: Total cost differences for the two case studies

		Peak Discharge Design (PDD)	Low Robustness Design (LRD)	High Robustness Design (HRD)
Case study 1	Total cost = Pipe costs € ($\times10^6$)	9.890	10.557	11.975
	Pressure violations (m)	0	218.64	1.87
	Demand violations (l/s)	0	341.71	1.62
	Difference in total costs	**0%**	**+7%**	**+21%**
Case study 2	Total cost € ($\times10^6$)	9.890	10.997	11.397
	Pipe costs € ($\times10^6$)	9.890	10.337	10.442
	Pump costs € ($\times10^6$)	0	0.659	0.975
	Pressure violations (m)	0	230.53	0.25
	Demand violations (l/s)	0	363.48	0.36
	Difference in total costs	**0%**	**+11%**	**+15%**

In terms of network behaviour, this design is sufficiently reliable to perform well even in the extreme scenarios. However, for normal working conditions the pipes are overdesigned, which means low velocities and high residence times, conditions that may lower water quality and safety. The option to raise the reliability of a water supply system to high levels only by increasing the pipe diameters should therefore be avoided if there are other alternatives that can be implemented.

The LRD for case study 2 is more costly than that for case study 1. These case studies show that, in terms of cost, for low robustness designs it is preferable to enlarge the pipes instead of using a PS. For less reliable solutions, a minor increase of pipe diameters is required for the network, which will be cheaper than implanting a pumping station downstream of the reservoir, even for low pumping heads.

Finally, the cost of the HRD for case study 2 is 15% higher than the PDD solution cost. This design is achieved both by increasing the pipe diameters and by using the PS to cope with the extreme scenarios. The combination of these elements resulted in a high robustness design for a lower cost increase than for case study 1. Furthermore, this approach reduces the overdesign problems. By introducing additional power at the reservoir, the PS avoids enlarging pipes to ensure the minimum desired pressures at the network nodes. In conclusion, these case studies indicate that for high robustness designs it is preferable to use a PS combined with a smaller enlargement of the pipes than to rely solely on changing the pipes.

4.5 Conclusions

To obtain high robustness solutions, water supply systems must be designed to cope with extreme operating conditions during their life cycle. The uncertainty related to future operating conditions should be taken into account early in the design stage. This work has presented a robust optimization model to help decision makers attain a good trade-off between reliability and cost. The performance of this method was illustrated by means of two case studies. The reliability of the water supply systems was ensured by two different strategies: 1st - designing the system to cope with the extreme operating conditions by increasing the pipe diameters; 2nd - designing the system for normal operating conditions and introducing a pumping station to deal with the extreme operating conditions.

This approach provides a new technique to reinforce a water supply system and also compares, in terms of costs, the solutions attained by different methods.. The case studies used to test the model led to the following conclusions: for low robustness solutions the 1st strategy was less expensive; if a high robustness solution is required then the 2nd strategy is less expensive. It must be also pointed out that the 1st strategy overdesigns the pipe diameters, leading to low velocities and high water residence times. The 2nd strategy, which is the innovation proposed in this work, can also be viewed as an alternative for existing water supply systems. For some existing systems, strengthening the infrastructure links may be difficult, namely if it involves construction works in urban areas, and it could also be prohibitively expensive. So, innovative strategies should be used. For future developments of this work, consideration of the water age can be added to the determination of solutions. The water quality could be used to evaluate the design alternatives so that the solution can be further optimized for a truly robust design. It could also be important to understand the influence of the maintenance costs of many pumping stations, required as contingence infrastructures in large systems, which is likely the case in real water systems. A life cycle cost analysis of the strategies (including the maintenance of pipes and pumps) can be conducted to choose the design of a robust solution.

Chapter 5

Using Real Options in the Optimal Design of Water Distribution Networks

This chapter presents an innovative real options approach to define an objective function to cope with some future scenarios considered in a specific case study. The objective of the model is to find a minimum cost solution for the first period of a planning horizon, while considering various possible future conditions that the network can cope with. The results of this work show that building flexibility into the decision strategy enables an adaptive approach to be taken that is able to avoid future lack of network capacity.

Keywords: water distribution networks, real options, simulated annealing.

5.1 Introduction

Over the last few decades water supply systems have been built with the aim of satisfying the increasing need for drinking water. The expansion of cities and population growth are causing a fast rise in the demand for water. The development of a community is intrinsically linked to its infrastructure. Urban infrastructure planning is an immense and complex task. According to Haimes (1998) the great challenge for the scientific community of the third millennium will be to develop tools and technologies to support and maintain infrastructure. Several methods for effective planning in the area of water systems have appeared in the literature. However, it is difficult to predict the future and a flexible plan is required to cope with its inherent uncertainty. In this context an approach called Real Options (ROs), originally from financial theory, could make an important contribution. Myers (1977) was the first to introduce the term Real Options (ROs), soon after the works of Black and Scholes (1973) and Merton (1973) which proposed a solution to the financial option valuing problem. Since then a large number of studies have been published where the concepts of ROs have been used in several fields. The ROs concept is analogous to financial options but ROs refer to physical assets such as buildings and infrastructure rather than financial instruments like stocks and shares.

Wang and Neufville (2004) divide ROs into two categories, ROs “on” systems and ROs “in” systems. ROs “on” systems focus on the external factors of a system and benefit from the use of financial valuation tools. On the other hand, ROs “in” systems incorporate flexibility into the structural design of a system and it is harder to value flexibility. This is the ROs category used to design water distribution networks.

The ROs approach facilitates adaptive strategies as it enables the value of flexibility to be included in the decision making process. Opportunities are provided for decision makers to modify and update investments when knowledge of future states is gained, which enables them to identify the most appropriate long term intervention strategies. All the processes capable of changing the operating conditions over the time horizon, functions of different possible scenarios, are processes where ROs analysis can be used. This concept gives a totally different perspective to a decision strategy, because there is no need for decisions to be inflexible and there is no specific date on which to take them. To summarize, ROs implies the right but not the obligation to take an investment decision. It permits flexibility in management, adapting response decisions to changing investment conditions.

A number of studies have developed ROs approaches to solve a variety of problems. Roberts and Weitzman (1981) analysed the nature of sequential investments during a time horizon. In industry He and Pindyck (1992) solve investment decisions with flexible production capacities. In petroleum exploration, Paddock *et al*. (1988) use ROs to evaluate the investment in an offshore platform. In electric power systems, Tannous (1996) compares flexible and rigid electrical systems. Other uses of ROs approaches include Nembhard and Aktan (2010), who systemized applications of ROs to design and develop engineering problems and de Neufville *et al*. (2006)a, reported the use of ROs in car parking problems. In the water industry, a ROs technique appears in the work of Woodward *et al*. (2011) to define maritime costal defenses to reduce the risk of flooding. In the area of water systems expansion, Suttinon and Nasu (2010) present an ROs based approach where the demand increases. Zhang and Babovic (2012) also use a ROs approach to evaluate different water technologies into water supply systems under uncertainty. There is a vast body of literature reporting the use of ROs but, until now, it has only been possible to find the work of Huang *et al*. (2010) that describes the application of ROs to the design of water distribution networks. The methodology used presents a flexible design tool based on decision scenario trees that reflect uncertainty associated with future demand for water. The authors used a genetic algorithm optimization model to find a flexible design to a simple case study. This work presents an innovative and different approach where uncertainty is not only associated with future demand for water, but also, considering new expansion scenarios for the network. The different possible network configurations during the planning horizon provide an alternative approach to how flexibility can be taken into account in the process of optimal design of water distribution systems.

The ROs approach *in* systems aims to provide flexibility to water distribution systems design to assist decision making over the uncertainty that management can face. According to Wang *et al*. (2004), this framework has two stages: option identification and option analysis. Option identification consists of trying to find all possible scenarios for the future planning horizon. The option analysis stage uses an optimization model to find good solutions for planning. This formulation enables decision makers to include more possible situations and develop explicit plans for the planning horizon.

The remainder of this study is organized as follows: in the next section the reasons for using ROs in water distributions networks are set out, together with an overview of the approach. This is followed by a case study to explain the method. A decision model is built and the results are shown. Then some comparisons are drawn with traditional approaches. Finally, the conclusions are systemized.

5.2 Why use Real Options in water distribution systems

Water distribution systems are costly and complex infrastructures which are meant to distribute water over a long planning horizon without interruption. Once built, networks cannot significantly change their operating conditions to adapt to new circumstances and the capacity and level of service cannot be increased easily. During the planning horizon, the pipe capacity declines as the roughness increases and the incidence of burst pipes also rises. Once laid, pipes cannot be reinforced without making large investments. Therefore, it is very important in water system planning to try to predict the future operating conditions. However, if the worst case scenario design is adopted the network could become overdesigned, with the result that resources are wasted and the water quality declines due to the lower velocity and higher water residence times. Moreover, cities are continually changing and the water supply systems have to be adapted for these changes. Sometimes a new urban or industrial area is built and the network has to be reinforced to accommodate the increased demand. But the opposite can also occur in areas whose population declines and the demand therefore falls. There are many sources of uncertainty in the future: technology, industry, economics, regulations and politics are some of them. It is very difficult to make correct forecasts under these uncertainties.

ROs analysis is an entire decision-making process that enhances the traditional decision analysis approaches. The benefits of flexible design relate to the facility to accommodate different future scenarios. But these benefits come at a cost. The flexibility to reconfigure a system will rarely come "for free" at the design stage, or be coincidentally available during the operation of a system without any prior provision. To prevent bad decisions, ROs can be very useful in the field of water distribution; more specifically, it enables: long term planning horizons, flexible planning, avoidance of future capacity reinforcement, quantification of the value of management flexibility and sparing of resources.

The ROs approach presented in this work uses a decision tree to reflect different scenarios that can occur during the planning horizon. The investment and the corresponding design of the network have to cope with the first period, but they have to work well throughout the planning horizon. The optimization process takes into account different kinds of scenarios. This work uses a method to find the optimal solution for the first period and to compute the value of the flexibility achieved by using a ROs approach. The model uses a minimum cost objective function and various scenarios are considered to predict different alternative future conditions. The objective function also includes a regret term used to approximate the cost of the ROs solution that must work well for all scenarios, with the cost of each scenario considered individually. Therefore, before running the model it is necessary to find the optimal solution for each scenario. The case study presented in section 5.3 explains how the ROs approach can be used and the benefits of using a flexible design.

5.3 Case study

In this section, a ROs approach is used in a simple case study. This is a water distribution network inspired in Taher and Labadie (1996) and is presented in Fig. 5.1. The characteristics of the pipes, nodes and the nodal demand conditions can be consulted in the aforementioned work.

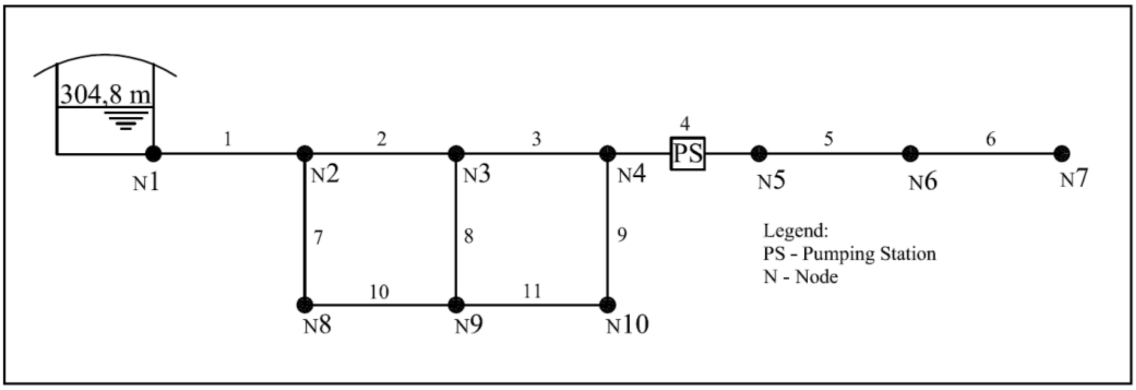

Figure 5.1: Water distribution network, inspired from Taher and Labadie (1996)

This is a simple new network with 10 nodes and 11 pipes supplied from a single reservoir with a free water surface elevation of 304.8 m. The pump placed at link 4 is used to increase pressure at the remote end nodes of the network. The efficiency of the pump is 80% and the daily consumption is of 12 hours at demand condition (1) and the other 12 hours at demand condition (2). Demand condition (3) considers the instantaneous peak discharge and a fire flow in node 10. The energy costs are € 0.18/kWh and should be evaluated for a 60-year period by a discount rate of 4% year. This rate was fixed based on the work of Wu *et al*. (2010). The design of the network considers the 11 different commercial diameters presented in table 5.1.

Table 5.1: Diameter, unit cost, Hazen-Williams coefficients

Diameters (mm)	Unit cost (€/m)	Hazen-Williams coefficients
100	87	125
125	97	125
150	102	125
200	120	125
250	147	125
300	157	125
350	187	125
400	215	125
450	247	125
500	277	125
600	371	125

A network planning horizon of 60 years was considered for this case study, which was split into 4 periods. This subdivision considers periods of different lengths. It is supposed that in the first period T=1, no modifications will be needed and that conditions will remain the same for the first 20 years. In this first step of the decision making process, the pipes in Fig. 5.1 and the head of the pumping station have to be designed for three different operating conditions. Periods T=2 and T=3, are short periods of 10 years each. The regional planning strategy assumes that the land use of some areas of the city is reviewed. Therefore, for T=2 the authorities are planning to license a new industrial area (NIA) if enough companies show an interest, and so, in this period, the network will be expanded in the proximities of the nodes 6 and 7. For T=3, it is expected that a new residential area (NRA) might grow close to the industries, due to labor required by the NIA, so the possible expansion of the network to the new residential area is considered. It is assumed that the pumps have to be changed every 20 years, so the pumps will have to be replaced in T=2 and T=4. In the last period, T=4, the demand should be predicted. However the time horizon is large and it is very difficult to accurately predict how demand will vary during the last 20 years of planning. For the last period it is assumed that the demand might increase between 0 and 20%, equally in all nodes in the network. The two different paths' scenarios that are possible in the last period are the 20% increase in demand and demand remaining constant. The potential expansion areas are shown in Fig. 5.2 and the characteristics of the new nodes and pipes are presented respectively in tables 5.2 and 5.3.

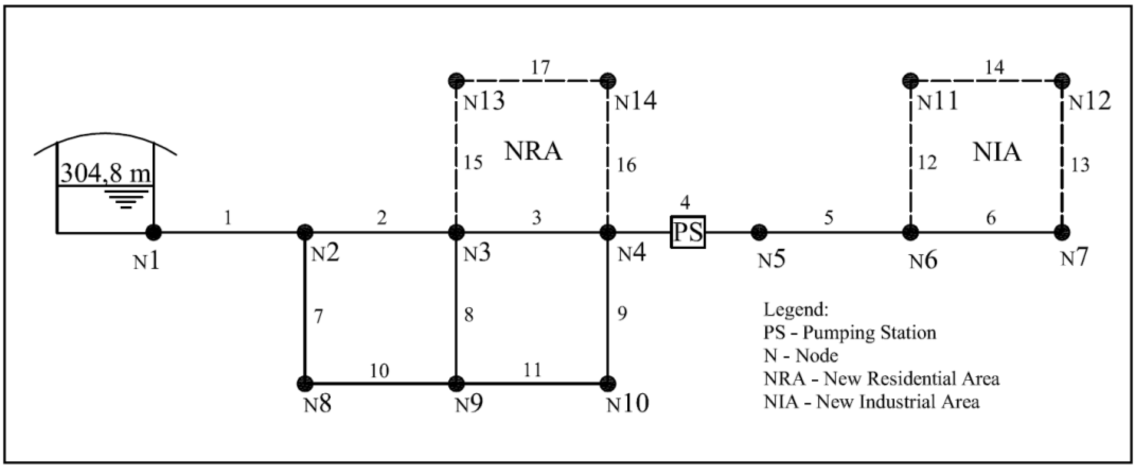

Figure 5.2: Water distribution network with possible expansion areas

Table 5.2: Characteristics of the new nodes

Node	Ground elevation (m)	Nodal consumption (l/s)			Minimum pressure (m)		
		(1)	(2)	(3)	(1)	(2)	(3)
11	298.56	18.927	13.249	18.927	35.0	35.0	14.0
12	289.56	31.545	22.082	31.545	35.0	35.0	14.0
13	243.84	18.927	13.249	18.927	35.0	35.0	14.0
14	243.84	12.618	8.833	12.618	35.0	35.0	14.0

Table 5.3: Characteristics of the new pipes

Pipe	Initial Node	Final Node	Length (m)
12	6	11	1609.344
13	7	12	1609.344
14	11	12	1609.344
15	3	13	1609.344
16	4	14	1609.344
17	13	14	1609.344

As the planning horizon progresses and the pipes get older their roughness increases. The planning horizon for this case study is 60 years and the fall in pipe capacity should not be neglected for any future decision that has to be made. Based on the DWSD (2004) report, the Hazen-Williams coefficients of ductile iron pipes decrease at a fixed rate of 2.5 per decade. Of course this rate depends on many factors and is also time dependent. But to simplify matters, a fixed rate was assumed for the entire planning horizon. The demand will also vary. It was assumed that for the first 40 years' operation the demand would increase at a constant rate of 10% per decade. For the last period, the demand could stabilize or increase by no more than 20%, as was supposed before.

Assuming a subdivided planning horizon, different conditions and possible expansions, a decision tree for all possible paths of the process and respective probabilities is shown in Fig. 5.3. There are 8 different paths that can be tracked during the planning horizon of the network. In the first period T=1 an initial design for the network is determined, in T=2 the pumps have to be replaced and a NIA may or may not need to be supplied. A NRA might be built in T=3. In the last period T=4, the pumps have to be replaced and the demand for the last 20 years of the planning horizon is designated.

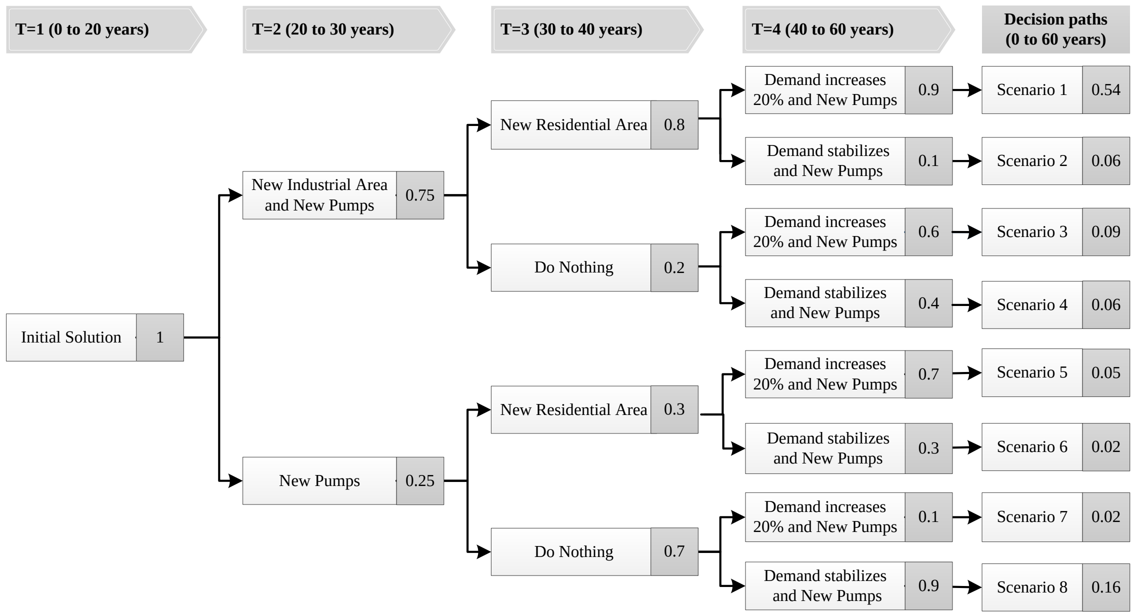

Figure 5.3: Decision tree for the planning horizon

The probabilities of the different scenarios are assigned to each path. These probabilities can be obtained by different methods, taking into account the urban planning and other plans for future developments and land use. Aggregating all the information, the probabilities can be given by experts. For this case study the probabilities considered for the different paths are shown in Fig. 5.3. In T=1, the probability of occurrence is 1; it is the only possibility. For T=2, it is accepted that there is a 75% chance that a NIA will be built. The probability that a NIA is not built is the other 25%. In T=3 it will be decided if the NRA will be extended or not. If the NIA has been installed then it is more probable that the NRA will be built because of the labor needed for the industries, so the probability of constructing the NRA is higher in the upper paths of the decision tree. In the last period, T=4, the demand has to be assigned. If the NIA or/and the NRA are built the probability of an increment in demand is higher. To conclude, the probability of the scenarios is calculated by multiplying the probabilities of all nodes on the path of that scenario, and they are shown in the last branches of the tree in Fig. 5.3.

5.4 Decision model

The decision model presented here is based on the ROs approach and aims to define an objective function to cope with all the different planning horizon paths that are considered in the case study. The objective function and the corresponding constraints of the model will determine a solution to implement in the first period, T=1, but taking into account all the possible future conditions that the network could cope with. The proposed objective function *OF* is given by expression 5.1:

$$OF = Min\ (\ Ci + Cf + R) \tag{5.1}$$

Where:

Ci - cost of the initial solution to be implemented in year zero (€);

Cf - cost of the future conditions (€);

R - regret term.

The objective function of Eq. 5.1 seeks to minimize not only the initial cost but also the probable future costs of the system. To take into account the differences between the costs of the general solution and the optimum costs for each scenario considered individually, a regret term is used in the objective function. The cost of the solution to implement is given by the sum of three terms. The term *Ci* computes the cost of the network for the first period T=1 of planning and is given by Eq. 5.2:

$$Ci = \left(\begin{array}{l} \sum_{i=1}^{NPI} \left(Cpipe_i (D_{i,1}) L_i \right) + \sum_{j=1}^{NPU} \left(Cps_{j,1} \right) + \\ + \left(\sum_{d=1}^{NDC} \left(Ce_d \cdot \sum_{j=1}^{NPU} \frac{\gamma \cdot QP_{j,d,1} \cdot HP_{j,d,1}}{\eta_j} \cdot \Delta t_d \right) \cdot 365 \cdot \frac{(1+IR)^{NY_1} - 1}{IR \cdot (1+IR)^{NY_1}} \right) \end{array} \right) \tag{5.2}$$

Where:

NPI- number of pipes in the network;

$Cpipe_i(D_{i,1})$ - unit cost of pipe i as function of diameter $D_{i,1}$ adopted (€/m);

$D_{i,1}$ - diameter of pipe i installed in period $T=1$ (mm);

L_i - length of pipe i (m);

NPU - number of pumps in the network;

$Cps_{j,1}$ - pumping station costs of pump j in the period $T=1$ (€);

NDC - number of demand conditions considered for the design;

Ce_d - cost of energy for demand condition d (€);

γ - specific weight of water (KN/m^3);

$QP_{j,d,1}$ - discharge of pump j for demand condition d and for period $T=1$ (m^3/s);

$HP_{j,d,1}$ - head of the pump j for the demand condition d and for period $T=1$ (m);

η_j - efficiency of pump j;

Δt_d - duration of demand condition d (h);

IR - annual interest rate for updating the costs;

NY_1 - number of years with the same conditions considered in period $T=1$.

The initial cost is given by the sum of the cost of the pipes, the cost of the pumps and the energy cost. These costs are computed assuming $NY_1=20$ which is the number of years of the first period. The other term of the objective function represents the future costs of all the decision nodes designs (Eq. 5.3) weighted by the respective probability of each decision node that is presented in Fig. 5.3:

$$Cf = \sum_{s=1}^{NS} \sum_{t=2}^{NTI} \left(Cfuture_{t,s} \cdot \prod_{nt=2}^{t} prob_{nt,s} \right) \tag{5.3}$$

Where:

NS - number of scenarios;

NTI - number of time intervals;

$Cfuture_{t,s}$ - cost of the future path of designs in scenario s for period t (€);

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

Adding up all possible future costs conditions, starting from T=2, multiplied by the probability of occurrence of such costs, we get a weighted mean of the future costs for the network. The term $Cfuture_{t,s}$ is computed in Eq. 5.4, for all periods beginning in T=2 (the costs for the first period are already calculated in the *Cinitial* term) and it is given by the sum of three terms:

$$Cfuture_{t,s} = \sum_{t=2}^{NTI} \left(\begin{array}{l} \sum_{i=1}^{NPI} \left(Cpipe_i(D_{i,t,s}) L_i \right) \cdot \frac{1}{\left(1+IR\right)^{Y_t}} + \sum_{j=1}^{NPU} \left(Cps_{j,t,s} \right) \cdot \frac{1}{\left(1+IR\right)^{Y_t}} + \\ + \left(\sum_{d=1}^{NDC} \left(Ce_d \cdot \sum_{j=1}^{NPU} \frac{\gamma \cdot QP_{j,d,t,s} \cdot HP_{j,d,t,s}}{\eta_j} \cdot \Delta t_d \right) \cdot 365 \cdot \frac{(1+IR)^{NY_t} - 1}{IR \cdot (1+IR)^{NY_t}} \right) \times \\ \times \frac{1}{\left(1+IR\right)^{Y_t}} \end{array} \right) \qquad (5.4)$$

Where:

$Cpipe_i(D_{i,t,s})$ - unit cost of pipe i as function of diameter $D_{i,t,s}$ (€);

$D_{i,t,s}$ - diameter of pipe i installed in period t for scenario s (mm);

Y_t - year when costs will be incurred for period t;

$Cps_{j,t,s}$ - pumping station costs of pump j in period t for scenario s (€);

$QP_{j,d,t,s}$ - discharge of pump j for demand condition d for period t and scenario s (m^3/s);

$HP_{j,d,t,s}$ - head of pump j for demand d for period t and for scenario s (m).

The first term of Eq. 5.4 computes the current value of the cost of the pipes to be installed in the different periods and scenarios, the second term computes the current value of the cost of the pumps for the different periods and for the different scenarios and finally the last term computes the current value of the cost of energy for each period and for each scenario. The pumping station costs are a function of the pump discharge and of the pump head.

So far, the first two terms of the objective function of Eq. 5.1 have been detailed. The sum of these two costs is intended to represent the full planning horizon cost of the network, considering future uncertainty. The other term of the objective function is given in Eq. 5.5 and computes the regret between the cost of the solution to implement and the optimal cost for each scenario:

$$R = \sum_{s=1}^{NS} \left\{ \left[\left(Ci + \sum_{t=2}^{NTI} Cfuture_{t,s} \right) - Coptimal_s \right]^2 \cdot \prod_{t=1}^{NTI} prob_{t,s} \right\} \cdot Nf \tag{5.5}$$

Where:

NS - number of scenarios;

$Coptimal_s$ - optimal cost design for scenario s (€);

Nf - normalization factor.

The term given by Eq. 5.5 aims to find solutions whose costs are as close as possible to all the individual optimal costs, with all the constraints being verified and performing well for all the scenarios. But the scenarios do not have the same probability of occurrence, so the weight of the situations more likely to occur should be higher. Therefore, these differences are multiplied by the probability of each path scenario.

5.5 Optimal solution for each scenario

The regret term shown in the objective function of Eq. 5.5, is based on the minimum cost solution for each scenario. Consequently, the model shown in Eq. 5.6 is used to find these solutions:

$$Min \sum_{t=1}^{NTI} \left(\begin{array}{l} \sum_{i=1}^{NPI} \left(Cpipe_i(D_{i,t})L_i \right) \cdot \dfrac{1}{(1+IR)^{Y_t}} + \sum_{j=1}^{NPU} \left(Cps_{j,t} \right) \cdot \dfrac{1}{(1+IR)^{Y_t}} + \\ + \left(\sum_{d=1}^{NDC} \left(Ce_d \cdot \sum_{j=1}^{NPU} \dfrac{\gamma \cdot QP_{j,d,t} \cdot HP_{j,d,t}}{\eta_j} \cdot \Delta t_d \right) \cdot 365 \cdot \dfrac{(1+IR)^{NY_t} - 1}{IR \cdot (1+IR)^{NY_t}} \right) \cdot \dfrac{1}{(1+IR)^{Y_t}} \end{array} \right) \quad (5.6)$$

The objective function is the sum of 4 periods of the current value of the costs of pipes, pumps and energy. The first term computes the present value of the pipe costs for the year zero. The second term computes the pumping stations' costs. Over the planning horizon the pumps have to be replaced every 20 years, so this cost has to be updated for the first operation year. Finally, the last term computes the cost of energy consumed by the pumps. The energy costs must be updated for each period of the planning horizon and then to the year zero. Adding up these costs for all 4 periods, we obtain the cost of pipes, pumps and energy for the whole planning horizon of the water network.

The constraints of the model are those usually considered in the optimal design of water distributions systems (Cunha and Sousa 1999). The method proposed here to solve the optimization model is a simulated annealing heuristic based on Aarts and Korst (1989), used by Cunha and Sousa (2001) and adapted for this work, linked to the EPANET (Rossman 2000) hydraulic simulator to verify the hydraulic constraints.

The design of the network has to satisfy minimum pressure constraints for 3 different demand conditions and for 4 different subintervals of the planning horizon. Thus the solution has to verify 12 different hydraulic conditions for each scenario. Table 5.4 shows the solutions for all the decision variables (DV) and the cost of each solution.

Table 5.4: Network design for the different scenarios

	DV	Scenarios							
		1	2	3	4	5	6	7	8
Pipes (mm)	1	600	500	600	500	500	500	450	500
	2	500	500	500	500	500	450	450	400
	3	500	450	450	450	400	400	400	400
	pump	-	-	-	-	-	-	-	-
	5	400	450	400	450	350	400	350	350
	6	200	300	300	200	250	250	250	250
	7	150	150	150	125	150	125	150	150
	8	150	150	150	200	200	200	150	200
	9	250	250	250	200	200	200	250	200
	10	100	100	100	100	100	100	100	100
	11	125	100	100	150	150	150	125	150
Pipes NIA (mm)	12	400	300	350	400	-	-	-	-
	13	150	300	200	150	-	-	-	-
	14	300	100	200	250	-	-	-	-
Pipes NRA (mm)	15	200	200	-	-	250	200	-	-
	16	150	150	-	-	100	125	-	-
	17	125	125	-	-	150	100	-	-
Pump 0-20 years (m)	H (1)	33	33	32	35	35	35	37	36
	H (2)	31	31	30	31	33	32	33	33
	H (3)	15	18	15	18	20	21	25	23
Pump 20-30 years (m)	H (1)	42	45	43	45	38	37	41	40
	H (2)	36	37	36	38	34	34	35	35
	H (3)	26	33	30	34	23	24	31	29
Pump 30-40 years (m)	H (1)	45	49	43	45	41	42	41	40
	H (2)	38	40	36	38	36	36	35	35
	H (3)	30	39	30	34	28	30	31	29
Pump 40-60 years (m)	H (1)	54	51	50	47	47	42	46	40
	H (2)	41	40	40	38	38	36	39	35
	H (3)	41	40	37	34	35	31	38	29
Construction cost (€)		3,992,269	3,682,766	3,794,636	3,512,817	3,242,176	3,215,033	2,937,053	2,975,677
Cost of energy (€)		1,190,024	1,156,966	1,163,855	1,137,703	756,193	717,879	779,515	733,601
Cost of the PS (€)		389,067	382,747	387,690	383,855	318,121	312,560	322,491	315,145
Total costs (€)		5,571,360	5,222,478	5,346,181	5,034,376	4,316,491	4,245,471	4,039,059	4,024,423

Table 5.4 presents the diameters in millimeters for each pipe in the network. The PS heights for all scenarios are presented after the pipe diameters. Finally the cost is shown subdivided into the cost of pipes, cost of energy and PS cost. All of these costs are updated for the year zero.

It is possible to draw some conclusions from Table 5.4. The pipe costs are the greatest percentage of the total costs. Another conclusion is that a decision about the increase of the demand has an impact on the pipe cost in the last period. It can be seen that if demand does not increase in the last period the cost of the pipes will be lower. This happens because, if there is a substantial increase of demand, the size of the pipes has to be larger and therefore the cost will be higher.

5.6 Results

The ROs approach presented in this study tries to minimize the costs by the objective function shown in Eq. 5.1. The model was solved for the case study and the results are presented in Fig. 5.4.

Decisions have to be made for each node of the decision tree. Fig. 5.4 presents, for each node, a table with the results of the design, beginning with the diameters in millimeters of the pipes to install in the network. Then the pump heads are presented for each of the three operating conditions considered in the case study and the costs are shown in the last lines, subdivided into the cost of the pipes, the pumps and energy. Finally the last branches of the decision tree present the total cost of the pipes, pumps and energy, updated for the year zero.

Fig 5.4 represents, for each scenario, the total amounts of investment and operating costs that will be expended if that scenario occurs. These future costs of the global solution can be compared with the optimal costs of each scenario. Fig. 5.5 shows this comparison and enables some conclusions to be achieved. First, the cost of the global solution is higher than the optimal cost of each scenario. In fact considering uncertainty in the process will increase the cost. If the future is well defined, the solution can be designed only for those conditions and not provide the flexibility to accommodate future alterations; the pipes and pumps can be designed to a specific capacity that will reduce the cost.

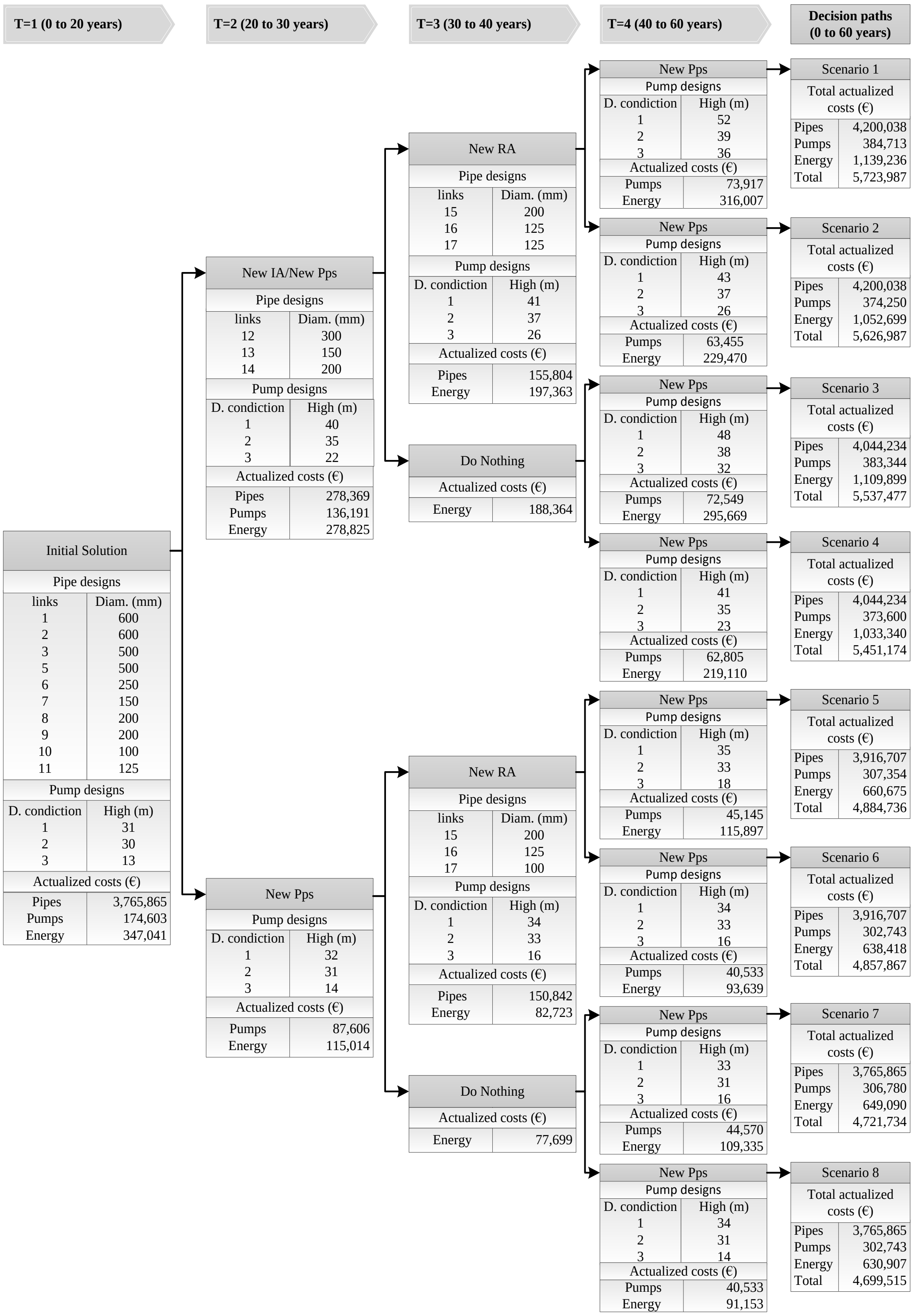

Figure 5.4: Solution for Real Options approach

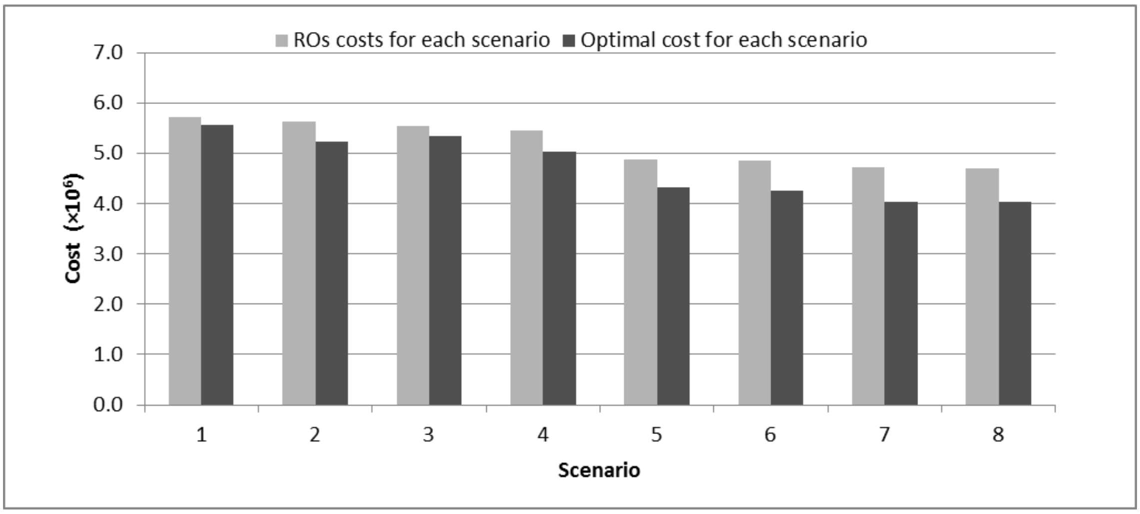

Figure 5.5: Cost comparison

Scenario 1 is the most likely to occur, $prob_1=0.54$, and it can be seen in Fig. 5.5 that the cost is very similar to the cost of the ROs solution for scenario 1. This proximity is due to the regret term used in the objective function in Eq. 1. The difference between the cost of the global solution and the optimal cost for each scenario is minimized by the regret term, but this difference is weighed with the probability of each scenario, and the scenarios with high probabilities will further penalize the objective function.

Finally, the expected cost of the solution is computed. The ROs approach considers different scenarios with different probabilities. By adding together all the future weighted costs presented in each node of the decision tree in Fig. 5.4 it is possible to achieve the present value of ROs solution, which is € 5,442,569. This is the expected cost for the case study considered for this work and is the sum of the initial solution cost, $Cinitial$ = € 4,287,509 that has to be implemented now plus the weighted costs of all the future options, $\sum_{s=1}^{NS}\sum_{t=2}^{NTI}\left(Cfuture_{t,s}\cdot\prod_{nt=2}^{t}prob_{nt,s}\right)$ = € 1,155,060. The decision makers can use this cost as the reference for the entire planning horizon operation of the system.

5.7 Comparing Real Option solutions

To understand the difference that using ROs will make in the flexible design of water distribution networks, a comparison between the ROs approach and a traditional design is made. The comparison presented covers the first 30 years of operation. The comparisons are presented in Fig. 5.6.

T=1 (0 to 20 years)

Initial Solutions		
Pipe designs	RO	traditional
links	Diam. (mm)	Diam. (mm)
1	500	400
2	400	350
3	400	350
5	400	300
6	350	200
7	150	150
8	150	100
9	250	250
10	100	125
11	100	100
Pump designs	RO	Traditional
D. condiction	High (m)	High (m)
1	36	46
2	32	37
3	24	47
Costs (€)	RO	Traditional
Pipes	3,075,456	2,576,560
Pumps	179,708	190,531
Energy	385,198	473,242
Total	3,640,362	3,240,333

T=2 (20 to 30 years)

New IA/New Pps		
Pipe designs	RO	Traditional
links	Diam. (mm)	Diam. (mm)
12	200	300
13	200	100
14	100	200
Pipe designs	RO	Traditional
links		Diam. (mm)
1		300
2		350
8		125
Pump designs	RO	Traditional
D. condiction	High (m)	High (m)
1	60	78
2	45	53
3	53	76
Costs (€)	RO	Traditional
Pipes	240,146	706,575
Pumps	150,579	161,037
Energy	396,504	497,731
Total	787,229	1,365,343

New Pps		
Parallel pipes	RO	Traditional
links		Diam. (mm)
8		200
Pump designs	RO	Traditional
D. condiction	High (m)	High (m)
1	40	59
2	35	41
3	28	61
Costs (€)	RO	Traditional
Pipes	0	88,138
Pumps	92,464	101,752
Energy	139,428	188,854
Total	231,892	378,744

Figure 5.6: Comparison between ROs and traditional design

Fig. 5.6 presents, for each node, a table with the results of the design, beginning with the diameters in millimeters of the pipes to be installed in the network. Then the pump heads are presented for each of the three operating conditions considered in the case study and the costs are shown in the last lines, subdivided into the cost of the pipes, the pumps and energy. These results are presented in two columns: ROs design and a traditional design.

The RO solution given in Fig. 5.6 is designed for the first period T=1, but considers 2 possible future scenarios: for T=2 a NIA either is installed with a probability of 75%, or it is not installed with a probability of 25%. Another design option for the first period T=1 is a solution planned only to function in the first 20 years of operation. This is the traditional design for this case study and does not take future uncertainty into account. Analyzing the solutions for the first time interval allows us to reach some conclusions. The ROs solution adopts larger pipe diameters than the traditional design, if only the first period is considered. The cost of the ROs solution is 12% higher than the cost of the traditional design solution. This cost increment is the initial price to pay to have a flexible solution that will perform well for the first 30 years of operation. The pump heads are higher for the traditional design solution due to the smaller diameters of the pipes next to the pumping station. Using larger diameters permits a reduction in head losses and, therefore, less energy is used to pump the water.

As has been shown, the ROs solution has a higher cost for the first period. However, the comparison has to cover the whole 30-year life and it was ascertained that the minimum pressures could not be satisfied in T=2 when the traditional design solution is adopted in the first period. Therefore, this solution has to be reinforced to satisfy the minimum pressure constraints. To compare the solutions, it was considered that the reinforcements can be made by using parallel pipes. The optimization problem assumes that these parallel pipes can be used for all the existing pipe links and considers that the unit pipe cost is the same as that given in Table 5.1.

To compare the designs the weighted cost of solutions for the 30-year planning horizon is used. The initial cost (Eq. 5.2) is added to the future weighted cost (Eq. 5.3) to obtain the value of € 4,288,757for the ROs design and the value of € 4,358,888 for the design that implies reinforcements of the network. This shows that the cost of the ROs design is 2% lower than for the inflexible design.

If the costs of the traditional design are compared with the ROs design for the 60-year planning horizon and if the decision path of scenario 1 (Fig. 5.3) is considered, a traditional design implies the expenditure of more than € 270,000 of the actualized costs. This solution includes the installation of 11 new parallel pipes. In fact, the ROs solution makes it possible to save on resources if an extended planning horizon analysis is performed.

From these comparisons it is also possible to conclude that the length of the planning horizon is very important for the initial design. However, the longer the planning horizon the more uncertainties arise and the design should be adjusted between different possible future scenarios. The ROs approach makes an important contribution because it can handle future uncertainty. But design flexibility has a cost. In this comparison, the ROs solution is 12% more costly than the traditional solution designed only for the first period. However, if a 30-year operation planning horizon is considered the ROs solution costs less than a solution that ignores different future possible scenarios. This is a proactive way to arrive at a minimum cost design solution for an extended planning horizon.

5.8 Conclusions

This work describes an innovative ROs approach used for a decision making process under uncertainty, in the field of water supply networks' design. The optimization model presented in this chapter tries to minimize costs over the whole planning horizon. Based on trying to delay some decisions for the future, ROs enables total investment to be reduced. But this delay comes at a cost. The initial solution has to be flexible enough to accommodate all the future conditions, and some pipes have to be overdesigned.

The design of a specific case study was used to explain the approach. Different options were considered for the infrastructure and the planning horizon was subdivided into periods with the aim of making midcourse corrections or additional investments. The results were presented by a decision tree, with the value for the different decision variables as well as the total amounts of investment and operating cost that will be expended. The future costs of the ROs solutions were compared with the optimal costs of each scenario.

To understand the difference provided by using ROs in the flexible design of water distribution networks, a comparison between the ROs approach and a traditional design was made. Results shows that the ROs solution makes it possible to save on resources if an extended and uncertain planning horizon analysis is performed.

The ROs philosophy tries to find opportunities to incorporate flexibility into decision making so as to mitigate the potential impact of future uncertainties, which in turn creates opportunities for adaptation. For the case study, an adaptable network design for a 60-year planning horizon had an extra initial cost, since a flexible solution is more costly than a solution that does not take the future uncertainty into account. However, the latter solutions will not have sufficient robustness to accommodate the future scenarios, and therefore some pipes in the network will need to be reinforced, for example by installing new parallel pipes. These reinforcements will of course increase the overall cost of the system over its entire planning horizon. The real value of ROs is their ability to adapt the solution to different future possible decisions.

Chapter 6

Using Real Options for an Eco-friendly Design of Water Distribution Systems

This chapter presents a real options approach to take into account the uncertainty during the entire life cycle of the hydraulic infrastructure. Furthermore, carbon emissions associated with the installation and operation of water distribution networks are considered. These emissions are computed according to an embodied energy based approach of the different materials used in water networks. A simulated annealing heuristic is used to optimize a flexible eco-friendly design of water distribution systems for an extended life horizon. This time horizon is subdivided in different time intervals in which different possible decisions paths can be followed. The proposed approach is applied to a case study and the results are presented according to a decision tree. Lastly some comparisons and results are made to demonstrate the quality of the results of this approach.

Keywords: optimization, water distribution networks, real options, simulated annealing

6.1 Introduction

Water supply and distribution systems represent a major investment for a society, whether it is in the construction of new systems or maintenance and rehabilitation of ageing infrastructure. For example, the cost of replacing ageing water infrastructure in the USA could reach more than $1 trillion over the next few decades (AWWA, 2012). These systems also have to cope with future uncertainties, including growing populations, shifting consumption patterns and a changing climate. Therefore, constructing and maintaining water infrastructure with the aim of improving reliability and reducing costs, represents a difficult problem to solve. Furthermore, there is a variety of associated environmental issues that should be addressed.

There's a rising concern about global warming. Nations will need to take actions to dramatically reduce greenhouse gas (GHG), namely, countries that have signed and ratified the Kyoto Protocol of 2009. 192 countries follow this protocol and have to limit and reduce carbon emissions over the next decades. In Portugal, the most pollutant industry is the electricity generation sector, based on ERSE (2012). Between 2005 and 2010, this sector was responsible for 55% of total carbon emissions.

Different definitions are being used for direct and indirect emissions. Alker *et al*. (2005) makes the distinction between direct emissions: those that water companies can control, and indirect emissions, those that are related to activities or operations not under the companies direct control. The electric energy consumed by the pumping station of the water networks is an example of indirect emissions.

Water supply systems are massive energy consumers. Energy is used to pump water from origins, during the treatment process and in pumping stations spread in the distribution networks. Manufacturing and installing pipes also consumes energy and produces carbon emissions. There are some procedures that allow minimizing the environmental impacts on water infrastructures. During the project and construction it is possible to choose the type of pipe material, to adopt pipe tracks that minimize the excavation, repaving and ecosystems deteriorations, to choose tank locations that minimize environmental impacts and to make an efficient management of water origins with the aim of reducing losses of water quantity and quality. During the operation, a careful maintenance should be made of all the network components as well as the well-functioning of the electro-mechanic equipment's. Furthermore, minimizing leaks and controlling pressure enables to reduce water losses. Reducing leaks permits to decrease both energy consumption and chemicals and raw water needs.

Pipes allow water transport in a quicker and continuous way, avoiding evaporation and contamination. But, building, maintaining and disposing pipes cause some environmental impacts that should be evaluated and minimized as much as possible. Building pipes in a traditional way implies opening long trenches. These trenches can be excavated in public roads or in forest ground. In both cases the inclusion of these elements causes disturbances in the ecosystems, in the surface and in the subsoil. Furthermore, the construction of some singularities like water treatment plants, tanks and pumping stations requires deforestation, soil movement, consumption of large quantities of materials and equipment's. Sometimes these singularities also cause important visual impacts. But the most import issue is related to the water taken from surface or underground origins that can be severely affected in terms of water quality and quantity due. Water quantity is reduced if the volume extracted is superior to the natural capacity to renovate the reserves. Quality can also decline for instance through saline intrusion due to pumping water on an aquifer near to the coast.

In the last decade, objectives focused on environmental aspects have started to be included in water distribution networks optimization works. Dandy *et al*. (2006) used an approach to minimize the material usage, embodied energy, and greenhouse gas emissions associated with the pipes. Wu *et al*. (2008) was the first to introduced greenhouse gas emissions minimization as an objective into the multiobjective optimal design of water networks. Only emissions from pipe manufacture were considered in this study. Herstein *et al*. (2011) presents an aproach considering environmental impacts in water systems design by an environmental impact index included in the environmental objective function of the optimization program. Shilana (2011) presents a life cycle assessment for two different pipe materials: ductile iron and reinforced concrete. The study was applied to a large diameter main water pipe. As results, the author presents the amount of carbon emissions and the tradeoff between water main pipe design alternatives.

This work considers a methodology to take into account not only the environmental impacts from pipe manufacturing, but also from other materials that are used during the construction of water networks. During construction, carbon emissions are related to the dimensions of the network. As pipe diameter increases, the quantity of material also increases, as well as the carbon emissions. Singular elements such as reservoirs, pumping stations, accessories and others will influence the carbon emissions. Furthermore, minimizing operating costs of the networks through the energy consumption will also minimize the carbon emissions of electricity generation.

The aim of this chapter it is to propose an approach that while taking into account environmental impacts, tries to find appropriate flexible solutions for the design and operation of water distribution systems. McConnell (2007) defined flexibility in systems as “the ability for a system to actively transform, or facilitate a future transformation, to better anticipate or respond to changing internal or external conditions”. These problems are challenging and very difficult to solve. Real options approach could give an important contribution in this field. Black and Scholes (1973) and Merton (1973) are the prior works that define and solve the financial option valuing problem. Then, Myers (1977) introduce the ROs. This approach permits flexible planning, thus allowing decision makers to adjust investment according to new future information. ROs has already been utilized, for example for: designing maritime security systems (Buurman *et al*. 2009); finding the optimal capacity for hydropower projects (Bockman *et al*. 2008); dam project investments (Michailidis and Mattas 2007); constructing a car park garage (De Neufville *et al*., 2006a), and designing satellite fleets (Hassan *et al*. 2005). However, there are very few papers on ROs concepts applied to water infrastructure: Woodward *et al*. (2011) used ROs for flood risk management and Zhang and Babovic (2012) used it for decision support in the design and management of a flexible water resources framework through innovative technologies.

In this introduction, a literature review was presented. The remainder of the chapter is organized as follows: in the next section a methodology to compute the carbon emissions of a water network is presented; next, the decision model is built and thereafter, a case study is presented to analyze the application of the methodology and to show some results. Finally some comparisons are made and conclusions are systemized.

6.2 Carbon emissions of water distribution systems

To incorporate carbon emissions costs in the design and operation of the water networks it is necessary to quantify emissions since the very beginning of the extraction of the different materials that are used until their final disposal. The water infrastructure is built and maintained using different materials. The most common are steel used in pipes, accessories and pumps; reinforced concrete in civil construction works like tanks, manholes and anchorages; plastic in pipes and accessories; aggregates in pipes backfill and asphalt for repaving. To evaluate the carbon emissions of these materials it is necessary to consider the whole life cycle that includes the extraction of the raw material, transport, manufacturing, assembling, installation, dissembling, destruction and/or decomposition. The embodied energy is determined by the sum of the energy (fuels, materials, human resources and others) that are used for product manufacturing and its use. The embodied energy tries to compute the sum of the total energy expended during all the life cycle of the product. The work of Hammond and Jones (2008) presents the embodied energy for the life cycle of some materials. Table 6.1 presents the embodied energy of the most common materials used in water infrastructures.

Table 6.1: Embodied energy of some materials used in water infrastructure

Material	Embodied energy	
	Mj/kg	KWh/kg
Ductile iron for pipes	34.40	9.56
Aggregates	0.11	0.03
Asphalt	6.63	1.84
Concrete	2.91	0.81
Structural steel	28.67	7.96

From the data collected from Hammond and Jones (2008) and presented in table 6.1, it is possible to compute the total amount of embodied energy necessary to build new pipes and reservoirs. The quantities of material used to install pipes are computed based on the scheme presented in Fig. 6.1. Some simplifications are assumed. The embodied energy to build the water network is achieved considering five different type materials: pipe material; aggregates to backfill pipes; asphalt for repaving, concrete and structural steel to build tanks. The units are expressed in KWh of energy per kg of material used.

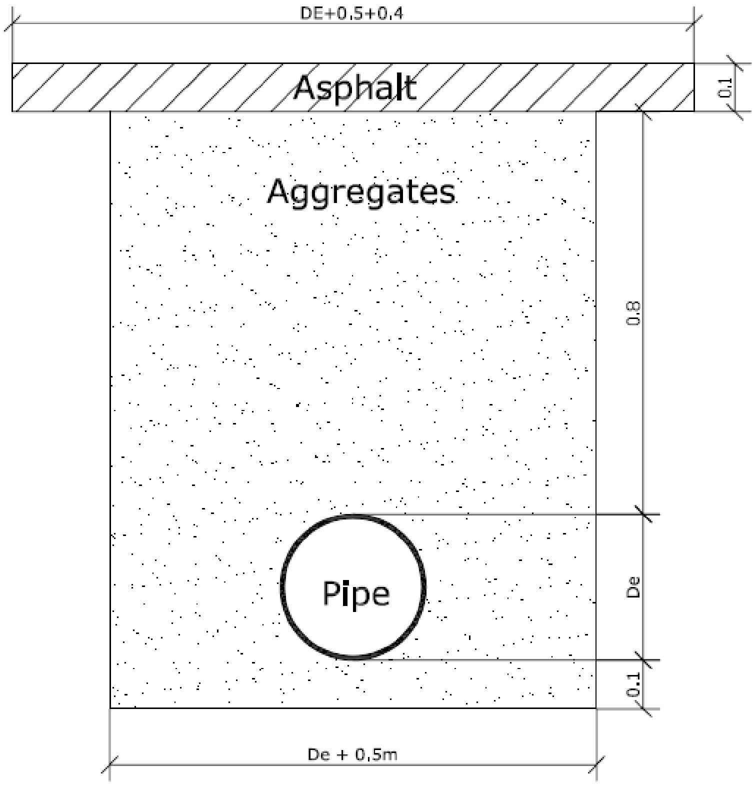

Figure 6.1: Scheme to compute the materials quantities

To determine the embodied energy of pipe construction by the traditional way, the quantity of energy per meter of pipe is considered. Therefore, it is required to compute the weight of the materials used to settle one meter of pipe. Considering the scheme presented in Fig. 6.1 is possible to compute the volume of aggregates and asphalt to use in each pipe meter settlement. The quantity of materials is function of the pipe diameter. This work adopts ductile iron pipes and to compute the embodied energy of the material Eq. 6.1 is used:

$$EEpipe_{Dc} = WDc \times EE_{iron} \quad (6.1)$$

Where:

$EEpipe_{Dc}$ - embodied energy of the pipe with commercial diameter Dc (KWh/m);

WDc - weight of the commercial diameter Dc (kg/m);

EE_{iron} - embodied energy of the ductile iron for pipes (KWh/kg);

The aggregates quantities are function of the commercial diameter to install. The width of the trench is equal to the external diameter of the pipes plus 0.5 m. The walls of the trench are considered to be vertical and the entire trench is fulfilled with aggregates. Based in these conditions, the quantity of embodied energy of aggregates is computed by Eq. 6.2:

$$EEaggr_{Dc} = \left\{ [(0.5 + ED_{Dc}) \times (0.1 + ED_{Dc} + 0.8)] \times 1 - \left(\frac{\pi \times DE_{Dc}^{2}}{4} \right) \times 1 \right\} \times W_{aggr} \times EE_{aggr} \quad (6.2)$$

Where:

$EEaggr_{Dc}$ - embodied energy of aggregates to backfill a pipe with diameter $Dc\,(KWh/m)$

ED_{Dc} - external diameter of the pipe with diameter *Dc (m)*;

W_{aggr} - weight of aggregates, equal to 2240 (kg/m^3);

EE_{aggr} - embodied energy of the material (KWh/kg);

Finally, the last material is asphalt. For extra repaving of each side of the trench 0.2 meter are considered. The embodied energy is computed by Eq. 6.3:

$$EEasphalt_{Dc} = \left\{\left[(0.5 + ED_{Dc}) + 0.2 + 0.2\right] \times 0.1 \times 1\right\} \times W_{asphalt} \times EE_{asphalt} \tag{6.3}$$

Where:

$EEasphalt_{Dc}$ - embodied energy of asphalt (KWh/m);

$W_{asphalt}$ - weight of the asphalt, equal to 2300 (kg/m^3);

$EE_{asphalt}$ - embodied energy of asphalt (KWh/kg);

To determine the total embodied energy (Eq. 6.4) per meter of pipe installation, Eq. 6.1, 6.2 and 6.3 are added:

$$EEtotal_{Dc} = EEpipes_{Dc} + EEaggr_{Dc} + EEasphalt_{Dc} \tag{6.4}$$

Where:

$EEtotal_{Dc}$ - total embodied energy of pipe installation (KWh/m);

Now the embodied energy can be computed for the different commercial diameters, considering the contribution of the ductile iron pipes, aggregates to involve the pipe and asphalt for repaving works. The carbon emissions related to the total embodied energy can be computed through Eq. 6.5:

$$CEpipe_{Dc} = EEtotal_{Dc} \times CET \tag{6.5}$$

Where:

$CEpipe_{Dc}$ - carbon emissions of pipe installation with commercial diameter Dc $(tonCO_2/m)$;

CET - total carbon emissions due to energy generation $(tonCO_2/KWh)$.

Carbon emissions are computed considering a value of CET=0.637×10^{-3} $tonCO_2$ per each KWh of energy produced. This is a mean value of the carbon emissions of electricity generation sector between 2005 and 2010 in Portugal (ERSE 2012).

This work also considered the carbon emissions related to the installation of new tanks in the network. New tanks are considered to be cylindrical with the same transversal area of 500 m^2. For a matter of simplification, the walls and the slabs of the tanks are assumed to have the same thickness, Fig. 6.2:

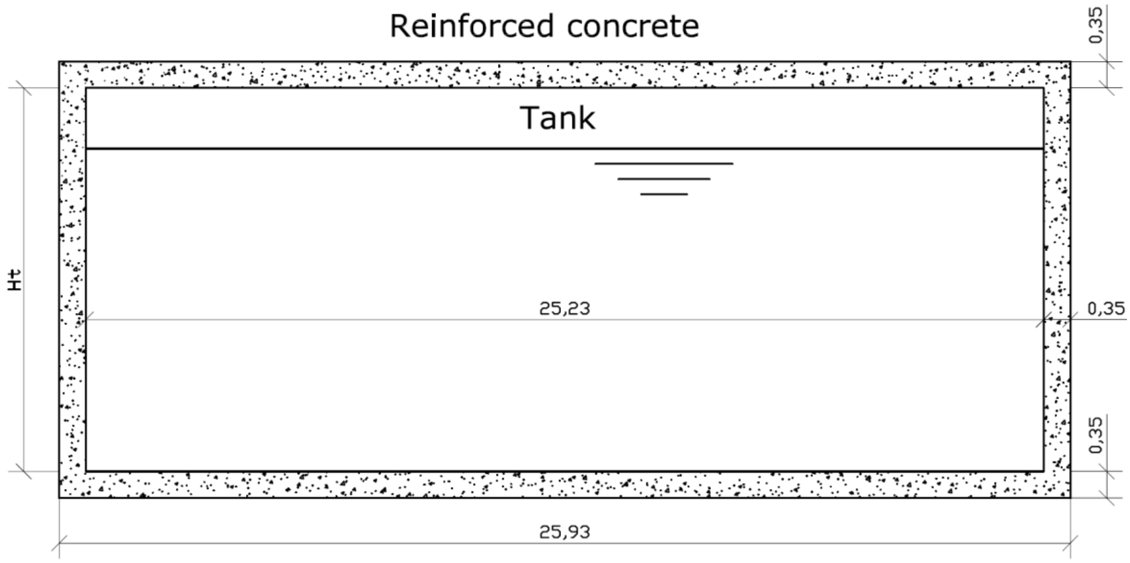

Figure 6.2: Scheme to compute the concrete quantities of tank constructions

The amount of concrete is a function of the volume of the tank. The thickness of the slabs and of the walls is considered to be equal to 0.35 m. Based on these conditions the quantity of embodied energy of concrete is computed by Eq. 6.6:

$$EETconcrete_t = \begin{bmatrix} \pi \times (r_b + Th_w)^2 \times Th_b) \times 2 + \\ + \pi \times Ht_t \left\{ (r_b + Th_w)^2 - r_b^{\ 2} \right\} \end{bmatrix} \times W_{concrete} \times EE_{concrete} \tag{6.6}$$

Where:

$EETconcrete_t$ - embodied energy of concrete of the tank t (KWh);

r_b - radius of the slab of the tank (*m*);

Th_w - thickness of the walls of the tank, equal to 0.35 (*m*);

Th_b - thickness of the slabs of the tank, equal to 0.35 (*m*);

Ht_t - height of the tank(m);

$W_{concrete}$ - weight of concrete, equal to 2500 $\left(kg/m^3\right)$;

$EE_{concrete}$ - embodied energy of concrete $\left(KWh/kg\right)$.

The embodied energy for reinforcing steel bars for concrete of tanks is also considered. For this study, the quantity of steal is considered to be a percentage of the cubic meters of concrete used in civil construction works, so the embodied energy of this material is given by Eq. 6.7:

$$EETsteel_t = \left[\pi \times \left(r_b + Th_w\right)^2 \times Th_b\right) \times 2 + \pi \times Ht_t \left\{\left(r_b + Th_w\right)^2 - r_b{}^2\right\}\right] \times Q_{steel} \times EE_{steel} \qquad (6.7)$$

Where:

$EETsteel_t$ - embodied energy of steel bars to build the tank t $\left(KWh\right)$;

Q_{steel} - quantity of steel per cubic meter of concrete, equal to 100 (kg/m^3);

$EEsteel$ - embodied energy of steel bars $\left(KWh/kg\right)$.

Summing the values given by Eq. 6.6 and 6.7, the carbon emissions of the tanks construction are determined through Eq. 6.8:

$$CETK_t = \left(EETconcrete_t + EETsteel_t\right) \times CET \qquad (6.8)$$

Where:

$CETK_t$ - carbon emissions of the tank t $\left(tonCO_2\right)$.

Beyond the emissions of pipes and tanks constructions, there are also important carbon emissions due to electric energy generation expended during the water infrastructure operation. Great amounts of energy are consumed and there are important carbon emissions that should be measured by the Eq. 6.9:

$$CEop = EC \times CET \tag{6.9}$$

Where:

$CEop$ - carbon emissions of energy in the operation of the network $(tonCO_2)$;

EC - energy consumption of the network during the operation (KWh);

Eq. 6.9 computes carbon emissions due to network operation. This work does not take into account carbon emissions related to other network elements that can be neglected when compared with pipe and tank construction.

Summing the partial contributions of pipes, tanks and the energy consumption, it is possible to achieve the total carbon emissions cost of the water network life cycle. This cost will be included in the optimization model presented in the next section.

6.3 Optimization model

During the life cycle of the water infrastructure, there are many possible scenarios that can occur. The future operation conditions of the water networks are uncertain. However, decisions have to be made and there are some constraints that increase even more the complexity of the problem. The water distribution networks optimization is a very complex task, because it aims to find a good solution in an enormous solution space. Furthermore, the decision variables are normally discrete, which increases the difficulty to find optimum solutions.

The approach developed in this work uses ROs to take into account different possible scenarios that can occur during the life cycle of the infrastructure. According to Wang *et al*. (2004), the ROs approach has two stages: option identification and option analysis. The options identification consists in trying to find all possible scenarios for the life horizon. The option analysis stage can use an optimization model to find possible solutions. This formulation enables decision makers to include more possible situations simultaneously and to develop different decision plans along the life cycle.

The objective function, *OF*, includes the minimization of costs and carbon emissions of the network implementation and operation. The objective function is presented in expression 6.10:

$$\begin{aligned} OF = Min \ \ Cinitial + \sum_{s=1}^{NS}\sum_{t=2}^{NTI}\left(Cfuture_{t,s} \cdot \prod_{nt=1}^{t} prob_{nt,s} \right) + \\ + \left[CEinitial + \sum_{s=1}^{NS}\sum_{t=2}^{NTI}\left(CEfuture_{t,s} \cdot \prod_{nt=1}^{t} prob_{nt,s} \right) \right] \cdot CEC \end{aligned} \quad (6.10)$$

Where:

Cinitial - cost of the initial solution to be implemented in year zero;

NS - number of scenarios;

NTI- number of time intervals for which the life cycle is subdivided;

$Cfuture_{t,s}$ - future design costs for time *t* and in scenario *s*;

$Prob_{nt,s}$ - probability of future design in time *nt* and in scenario *s*;

CEinitial - carbon emissions of the initial solution to be applied in year zero;

$CEfuture_{t,s}$ - carbon emissions for time t and in scenario s;

CEC - Carbon emissions cost.

The objective function given by Eq. 6.10 has to find the first stage solution, T=1, and to find future decisions to implement. The objective function is given by the sum of different terms. The initial solution cost is given by Eq. 6.11:

$$Cinitial = \left(\begin{array}{l} \sum_{i=1}^{NPI}\left(Cpipe_i(D_{i,1})L_i\right) + \sum_{t=1}^{NT} CT_t + \sum_{i=1}^{NPI}\left(Creab_i(D_{i,1})L_i\right) + \sum_{j=1}^{NPU}\left(CEps_{j,1}\right) \\ + \left(\sum_{d=1}^{NDC}\left(Ce_d \cdot \sum_{j=1}^{NPU} \frac{\gamma \cdot QP_{j,d,1} \cdot HP_{j,d,1}}{\eta_j} \cdot \Delta t_d \right) \cdot 365 \cdot \frac{(1+IR)^{NY_1}-1}{IR\cdot(1+IR)^{NY_1}} \right) \end{array} \right) \tag{6.11}$$

Where:

NPI - number of pipes in the network;

$Cpipe_i(D_{i,1})$ - unit cost of the pipe i as function of the diameter $D_{i,1}$ adopted;

$D_{i,1}$ - diameter of the pipe i installed in the time interval $T=1$;

L_i - length of the pipe i;

NT - number of new tanks of the network;

CT_t - cost of the tank t;

$Creab_i(D_{i,1})$ - unit cost to rehabilitate the existing pipe i as function of the diameter $D_{i,1}$;

NPU - number of pumps in the network;

$CEps_{,j,1}$ - equipment costs of the PS j for the time interval $T=1$;

NDC - number of demand conditions considered for the design;

Ce_d - cost of energy for demand condition d;

γ - specific weight of water;

$QP_{j,d,1}$ - discharge of the pump j for demand condition d and for time interval $T=1$;

$HP_{j,d,1}$ - head of the pump j for demand condition d and for time interval $T=1$;

η_j - efficiency of the pump j;

Δt_d - extent in hours for demand condition d;

IR - annual interest rate for updating the costs;

NY_t - number of years with the same conditions considered for time interval $T=1$.

The term $Cinitial$ (eq. 6.11) computes the network costs for the first stage. This term is given by the sum of the costs of pipes, the costs of the tanks, the rehabilitation costs of the existing pipes, the equipment costs of new pumps and the present value cost of energy. The pump cost is given by Eq. 6.12:

$$CEps = 700473.4 Q^{0.7} H_m^{0.4} \tag{6.12}$$

Where:

$CEps$ - costs of the pump;

Q - flow of the pump (m^3/s);

H_m - head of the pump (m).

The other term of the objective function is given by the weighted sum of the future costs. The future cost is computed by Eq. 6.13:

$$Cfuture_{t,s} = \begin{pmatrix} \sum_{i=1}^{NPI}\left(Cpipe_i(D_{i,t,s})L_i\right)\cdot\frac{1}{\left(1+IR\right)^{Y_t}} + \sum_{j=1}^{NPU}\left(CEps_{j,t,s}\right)\cdot\frac{1}{\left(1+IR\right)^{Y_t}} + \\ +\left(\sum_{d=1}^{NDC}\left(Ce_d\cdot\sum_{j=1}^{NPU}\frac{\gamma\cdot QP_{j,d,t,s}\cdot HP_{j,d,t,s}}{\eta_j}\cdot\Delta t_d\right)\cdot 365\cdot\frac{(1+IR)^{NY_t}-1}{IR\cdot(1+IR)^{NY_t}}\right)\cdot\frac{1}{\left(1+IR\right)^{Y_t}} \end{pmatrix} \quad (6.13)$$

The future cost is computed for all time intervals beginning at T=2 (for the first time interval, the costs are already computed) and is given as the sum of three terms. The first term computes the present value costs of the pipes to be implanted in the different time intervals and scenarios, the second term computes the present value equipment costs of the pumps for the different time intervals and for the different scenarios and finally the third term computes the present value of costs of energy for each scenario.

The sum of the initial and the future costs represents the network cost for the entire time horizon, considering future uncertainty. The probabilities for the different scenarios are computed by the product of the probabilities of the decision nodes in each path for all the time periods.

To finish, a term to compute the environmental impacts of the water supply system is also added. This term is computed by the sum of two terms multiplied by the carbon emission cost, *CEC*. These terms are introduced in Eq 6.14 and 6.15.

$$CEinitial = \begin{pmatrix} \sum_{i=1}^{NPI}\left(CEpipe(D_{i,1})L_i\right) + \sum_{t=1}^{NT}CETK_t + \\ +\sum_{d=1}^{NDC}\left(CET\cdot\sum_{j=1}^{NPU}\frac{\gamma\cdot QP_{j,d,1}\cdot HP_{j,d,1}}{\eta_j}\cdot\Delta t_d\right)\cdot 365\cdot NY_1 \end{pmatrix} \quad (6.14)$$

$$CEfuture_{t,s} = \left(\begin{array}{l} \sum_{i=1}^{NPI} \left(CEpipe(D_{i,t,s}) L_i \right) + \\ + \left(\sum_{d=1}^{NDC} \left(CET \cdot \sum_{j=1}^{NPU} \frac{\gamma \cdot QP_{j,d,t,s} \cdot HP_{j,d,t,s}}{\eta_j} \cdot \Delta t_d \right) \cdot 365 \cdot NY_t \right) \end{array} \right) \tag{6.15}$$

Eq. (6.14) computes the total carbon emissions for the first operation period and Eq. (6.15) computes the carbon emissions for the different future scenarios weighted by their probability of occurrence. The initial carbon emissions are calculated by adding the carbon emissions related to the pipe installation, the tanks construction and the energy consumptions. The carbon emissions in the future scenarios are computed by a similar procedure. These emissions are multiplied by the unit carbon emission cost CEC. It should be noted that the carbon emissions costs are not actualized as a zero discount rate should be used for carbon emissions (Wu *et al*., 2010). This based on the recommendation of the Intergovernmental Panel on Climate Change (IPCC).

The objective function represents the network cost for the entire time horizon. Some decisions have to be taken now, but there are also some others that can be delayed and can be taken only when future uncertainties are determined. The ROs framework permits to design water infrastructures delaying some decisions to the future.

6.4 case study

With the objective of demonstrating the application of the ROs approach, a well-known water network is considered. This work uses a case study based on a hypothetical network inspired by Walski *et al*. (1987). The network aims to represent a small and old city, Fig. 6.3.

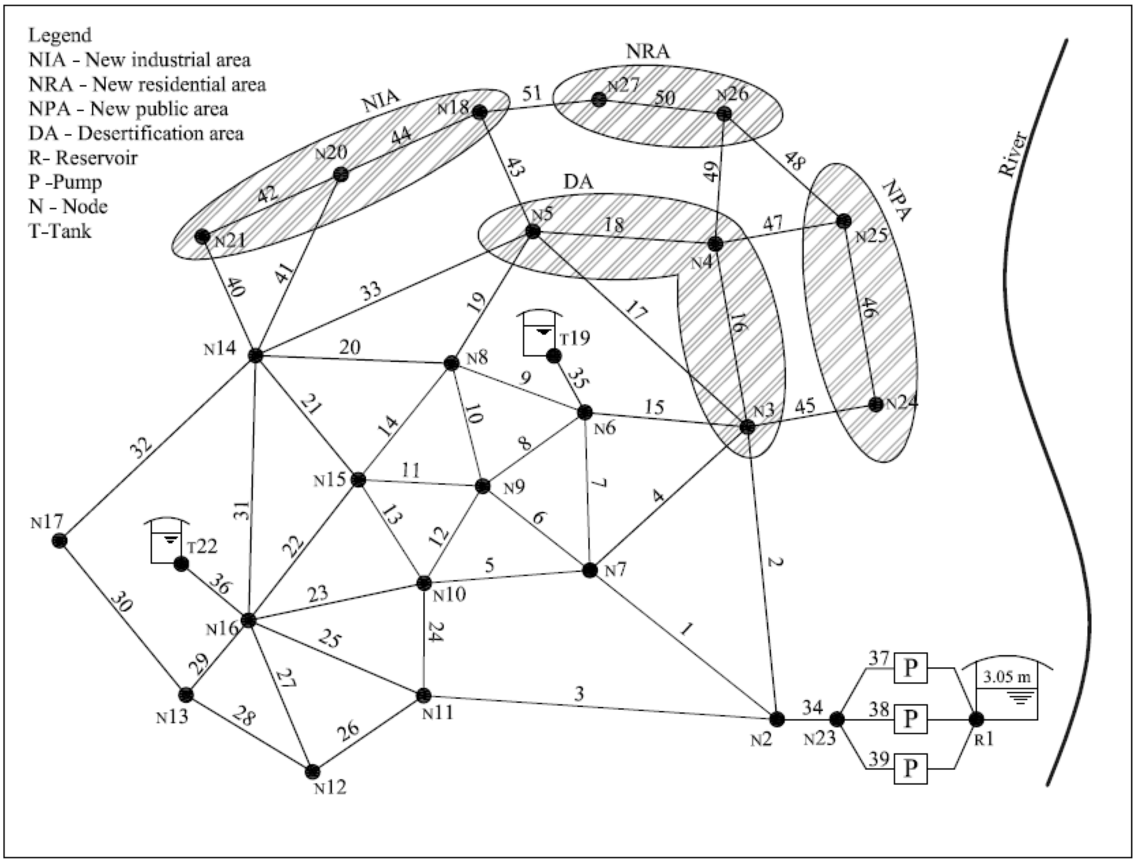

Figure 6.3: Scheme of the network (inspired from Walski *et al*. 1987)

Fig. 6.3 shows a water distribution network planned for the next 60 years. However, this planning horizon is subdivided in 3 time intervals of 20 years. In the first 20 years of operation, some decisions have to be made. It is considered that the water company needs to improve the network capacity to satisfy future demand during the first time interval of 20 years. However, 8 different possible future scenarios could be considered as presented in Fig 6.4.

This work considers different expansion areas. For T=2 authorities are planning to build a new industrial area (NIA) and a new public services area (NPA) with some facilities near the river, therefore, the network can be extended in this time interval for two different areas. For T=3 it is also predicted that a new residential area (NRA) can grow in the proximity of the industries and public services, due to the labor required by the new industries as well as in the public services occupations. However, if these areas will not be built, it is probable that the city gets a depopulated area near the river and the water consumption is likely to decrease to 75%. These areas are shown in Fig. 6.3.

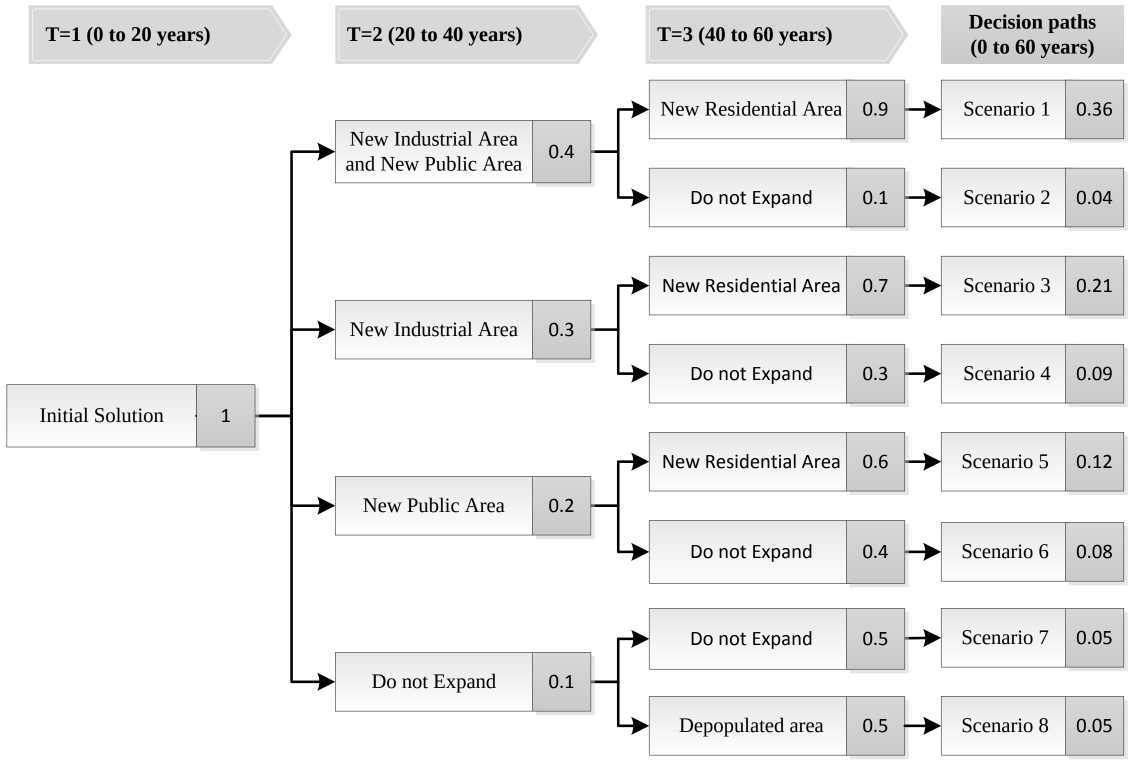

Figure 6.4: Decision tree and probabilities of occurrence for the life cycle

Finally it is required to suggest probabilities for each path of the different scenarios. For the case study probabilities for the different paths of the systems are proposed, as shown in the boxes of Fig. 6.4. The probabilities of the scenarios are computed by the product for all the time periods of the decision node probabilities in each path.

The network has two existing tanks operating with water levels between the elevations of 65.53 m and 77.22 m and with a capacity of 1,136 m^3 each, but according to the original case study, the company wants to operate the tanks between the levels

68.58 and 76.20 m. The volume between 65.53 m and 68.58 m is used for emergency needs, a volume equal to 284 m^3 in each tank. At all nodes a minimum pressure of 28.14 m is required for average day flow conditions, and the instantaneous peak flow is given as the average nodal demand multiplied by 1.8. The system is also subject to three different firefighting conditions lasting two hours of each. The minimum nodal pressures during firefighting conditions are 14.07 m. The firefighting conditions are: 157.73 l/s at node 9; 94.64 l/s at nodes 18, 20, 21; and 63.09 l/s at nodes 12 and 16. These fire flows should be met simultaneously with a daily peak flow equal to 1.3 times the average flow. All the pressure requirements should be assured with one of the pumps out of service and the tanks at the minimum levels after a normal operation day.

To solve this problem it is necessary to consider simultaneously the design and operation of the network. The city is shaped around an old center located to the south east of link 14. In this area, excavations are more costly than in other areas. There is an adjacent residential area with some existing industries near node 16. The reinforcement possibilities are duplication of existing pipes, cleaning and lining existing pipes, implantation of new pumps and building new tanks. The city is supplied from a water treatment plant and by three existing identical pumps connected in parallel. Pumps have to be replaced every 20 years but according to the original case study, for the first time interval pumps already exist and there is no cost associated with installation. The possibility of installing 2 additional pumps in parallel is considered if additional capacity is required. The water treatment plant is maintained at a fixed level of 3.048 m. The characteristics of the links are given in table 6.2.

Table 6.2: Characteristics of the pipes

Pipe	Initial node	Final node	Lenght (m)	Existing diameter	Area
1	2	7	3657.60	406.4	Urban
2	2	3	3657.60	304.8	Residential
3	2	11	3657.60	304.8	Urban
4	7	3	2743.20	304.8	Residential
5	7	10	1828.80	304.8	Urban
6	7	9	1828.80	254.0	Urban
7	7	6	1828.80	304.8	Urban
8	6	9	1828.80	254.0	Urban
9	6	8	1828.80	304.8	Urban
10	8	9	1828.80	254.0	Urban
11	9	15	1828.80	254.0	Urban
12	9	10	1828.80	254.0	Urban
13	10	15	1828.80	304.8	Urban
14	8	15	1828.80	254.0	Urban
15	3	6	1828.80	254.0	Residential
16	3	4	1828.80	254.0	Residential
17	3	5	2743.20	254.0	Residential
18	4	5	1828.80	254.0	Residential
19	5	8	1828.80	254.0	Residential
20	8	14	1828.80	254.0	Residential
21	14	15	1828.80	203.2	Residential
22	15	16	1828.80	203.2	Residential
23	10	16	1828.80	203.2	Residential
24	10	11	1828.80	203.2	Urban
25	11	16	1828.80	254.0	Residential
26	11	12	1828.80	203.2	Residential
27	12	16	2743.20		New
28	12	13	1828.80	203.2	Residential
29	13	16	1828.80	254.0	Residential
30	13	17	1828.80	203.2	Residential
31	14	16	1828.80	203.2	Residential
32	14	17	3657.60	203.2	Residential
33	5	14	3657.60	203.2	Residential
34	2	23	30.48	762.0	Urban
35	6	19	30.48	304.8	Urban
36	16	22	30.48	304.8	Residential
37	1	23	Pump		
38	1	23	Pump		
39	1	23	Pump		
40	14	21	1828.80		New
41	14	20	1828.80		New
42	20	21	1828.80		New
43	5	18	1828.80		New
44	18	20	1828.80		New
45	3	24	1828.80		New
46	24	25	1828.80		New
47	4	25	1828.80		New
48	25	26	1828.80		New
49	4	26	1828.80		New
50	26	27	1828.80		New
51	27	18	1828.80		New

The average daily water demand for nodes is presented in table 6.3 as well as the elevation of the nodes and existing tanks.

Table 6.3: Characteristics of the nodes

Node	Elevation (m)	Average day demand (l/s)	Node	Elevation (m)	Average day demand (l/s)
1	3.05	WTP	15	36.58	24.236
2	6.10	31.545	16	36.58	63.090
3	15.24	12.618	17	36.58	25.236
4	15.24	12.618	18	24.38	37.854
5	15.24	37.854	19	65.53	Tank
6	15.24	31.545	20	24.38	37.854
7	15.24	31.545	21	24.38	37.854
8	15.24	31.545	22	65.53	Tank
9	15.24	63.090	23	3.05	0.000
10	15.24	31.545	24	15.24	37.854
11	15.24	31.545	25	15.24	37.854
12	36.58	24.236	26	15.24	12.618
13	36.58	24.236	27	15.24	12.618
14	24.38	24.236			

The demand varies during an operating day. Table 4 presents the demand variation during 24 hours. For example, between 0 – 3 hours the demand is 70% of the average daily demand.

Table 6.4: Variation of the demand during the 24 hours of operation

Daily period	Demand
0 - 3h	0.7
3 - 6h	0.6
6 - 9h	1.2
9 - 12h	1.3
12 - 15h	1.2
15 - 18h	1.1
18 - 21h	1.0
21 - 24h	0.9

It is possible to duplicate or clean and line 35 existing pipes. There are also 13 new links in the expansion areas. The commercial diameters and the unit costs of new pipes, cleaning and lining are presented in table 6.5, as function of the network area.

Table 6.5: Diameters and unit cost

Pipe diameter (mm)	Unit costs				
	Installation of pipes			Clean and line existing pipes	
	Urban ($/m)	Residential ($/m)	New ($/m)	Urban ($/m)	Residential ($/m)
152.4	85.958	46.588	41.995	55.774	39.370
203.2	91.207	64.961	58.399	55.774	39.370
254.0	111.877	82.349	73.819	55.774	39.370
304.8	135.827	106.299	95.801	55.774	42.651
355.6	164.698	131.890	118.766	59.711	46.588
406.4	191.929	159.121	143.045	64.961	50.853
457.2	217.192	187.664	168.963	70.866	56.102
508.0	251.969	219.160	197.178	77.100	66.273
609.6	358.268	280.512	252.625	98.753	
762.0	467.520	380.906	346.129	135.499	

If a pipe has been cleaned and lined, the Hazen-Williams coefficient becomes equal to C=125 and if it is a new pipe it is equal to C=130. During the life cycle, pipes get older and the wall roughness increases. Based on the DWSD (2004) report, the Hazen-Williams coefficients of ductile iron pipes decreases at a fixed rate of 2.5 per decade. Obviously this rate depends on many kinds of different conditions and it is also time dependent. But to simplify the problem, this work considers a fixed rate during the life cycle.

The 24 hour operation of the network is subdivided in 1 hour time steps. Three existing pumps have to supply the daily needs. This work considers the possibility to install two additional parallel pumps due to the new areas to be built. The number of the pumps during the 24 hours results in additional variables to solve in the optimization problem in each time interval and for each scenario. Table 6 gives five points of the characteristic curves for each pump. These curves are equal to the original case study.

Table 6.6: Function points of each pump

Flow (l/s)	Pump head (m)	Efficiency (%)
0	91.5	0
126.2	89.1	50
252.4	82.4	65
378.5	70.2	55
504.7	55.2	40

The energy costs are equal to 0.12$ per KWh. The present value costs are computed using a discount rate of 4% during the life cycle. According to Wu *et al*. (2010) the definition of discount rates is a very complex issue and they normally vary between 2 and 10%. This work adopts a 4% rate to emphasize the importance of the future costs in the decision making process. There is also the possibility to install new tanks at the nodes in the network. Tanks are connected to nodes by a short pipe with a length of 30.48m and a variable pipe diameter. Tanks costs are function of the volume and are given in table 6.7. These data are equal to the original case study.

Table 6.7: Tank costs

Volume (m^3)	Cost $\times 10^3$ ($)
227.3	115
454.6	145
1136.5	325
2273.0	425
4546.0	600

Finally, it is considered that the tank installation and rehabilitation of the existing pipes can only be made in the first time interval and have to perform well with all the possible future conditions expressed in Fig. 6.5. Based on Eq. 6.4, the embodied energy is calculated for different commercial diameters used in this work and is showed in table 6.8.

Table 6.8: Embodied energy and carbon emissions of commercial diameters installation

Diameters (mm)	Ductile iron pipes (KWh/m)	Aggregates (KWh/m)	Asphalt (KWh/m)	Embodied energy (KWh/m)	Total emissions (tonCO_2/m)
152.4	269.88	44.91	445.38	760.17	0.48
203.2	406.20	49.95	466.87	923.03	0.59
254.0	575.89	55.07	488.37	1119.33	0.71
304.8	705.15	60.26	509.87	1275.27	0.81
355.6	776.37	65.52	531.37	1373.26	0.87
406.4	890.32	70.86	552.87	1514.05	0.96
457.2	1004.37	76.27	574.37	1655.01	1.05
508.0	1118.33	81.75	595.87	1795.95	1.14
609.6	1346.24	92.95	638.86	2078.05	1.32
762.0	1688.10	110.30	703.36	2501.77	1.59

Table 6.8 shows the embodied energy computed for the different commercial diameters, considering the contribution of ductile iron of pipes, aggregates for pipe bedding and asphalt for repaving works. The last column of the table represents the carbon emissions of the total embodied energy. The optimization model introduced here has the objective to minimize the installation costs of pipes, pumps and tanks, the energy costs and the carbon costs. The cost per carbon tonne emitted is assumed to be 5$.

6.5 Results

This work includes an approach that uses ROs to minimize life cycle costs of water distribution systems considering uncertainty. When a long life design horizon is considered, the future is unknown. The water demand will certainly vary considerably. New urban areas can be built and other areas can become depopulated. The ROs approach can deal with these uncertainties and can provide to decision makers good design solutions for flexible water networks. This work uses a decision tree with 8 possible different scenarios that can occur during the 60 years life cycle. However, it is only necessary to decide the configuration of the network for the first time period of 20 years. The solution of this period should work well in the first stage, but taking into account futures needs. This is a robust solution that will be adapted in the subsequent time intervals according to the evolution of the circumstances.

The model is solved using the hydraulic simulator EPANET (Rossman, 2000) to verify the hydraulic constraints. A simulated annealing heuristic (Aarts and Korst 1989) is used as the optimization method. Simulated annealing can be successfully used in discrete and large search space. The method used in this study is based on the work by Cunha and Sousa (1999). Fig. 6.5 gives the solution achieved by the approach described. The results are represented in a life cycle tree with the same shape of the decision making alternatives reproduced in Fig. 6.4.

Fig. 6.5 summarizes the design achieved for the case study. For each node a table is presented with the results of the design, starting by showing the pipe rehabilitation decisions, the new parallel pipes and the tank locations and capacities. The present value costs are subdivided into costs of the pipes, tanks, pumps, energy, carbon emissions and total costs. The last branches of the decision tree represent the total life cycle costs, for each of the different scenarios.

It can be concluded from the results that the life cycle cost is dependent on the decisions that are taken during the time intervals. However, the first time interval 0-20 years accounts for most of investment costs. In this time interval, the network will be reinforced with some new parallel pipes, with new tanks and with cleaning and lining of existing pipes. These total costs take into account the carbon emissions due to the installation of pipes and tanks and due to energy consumption. The solution for scenario 1 is schematized in figure 6.6.

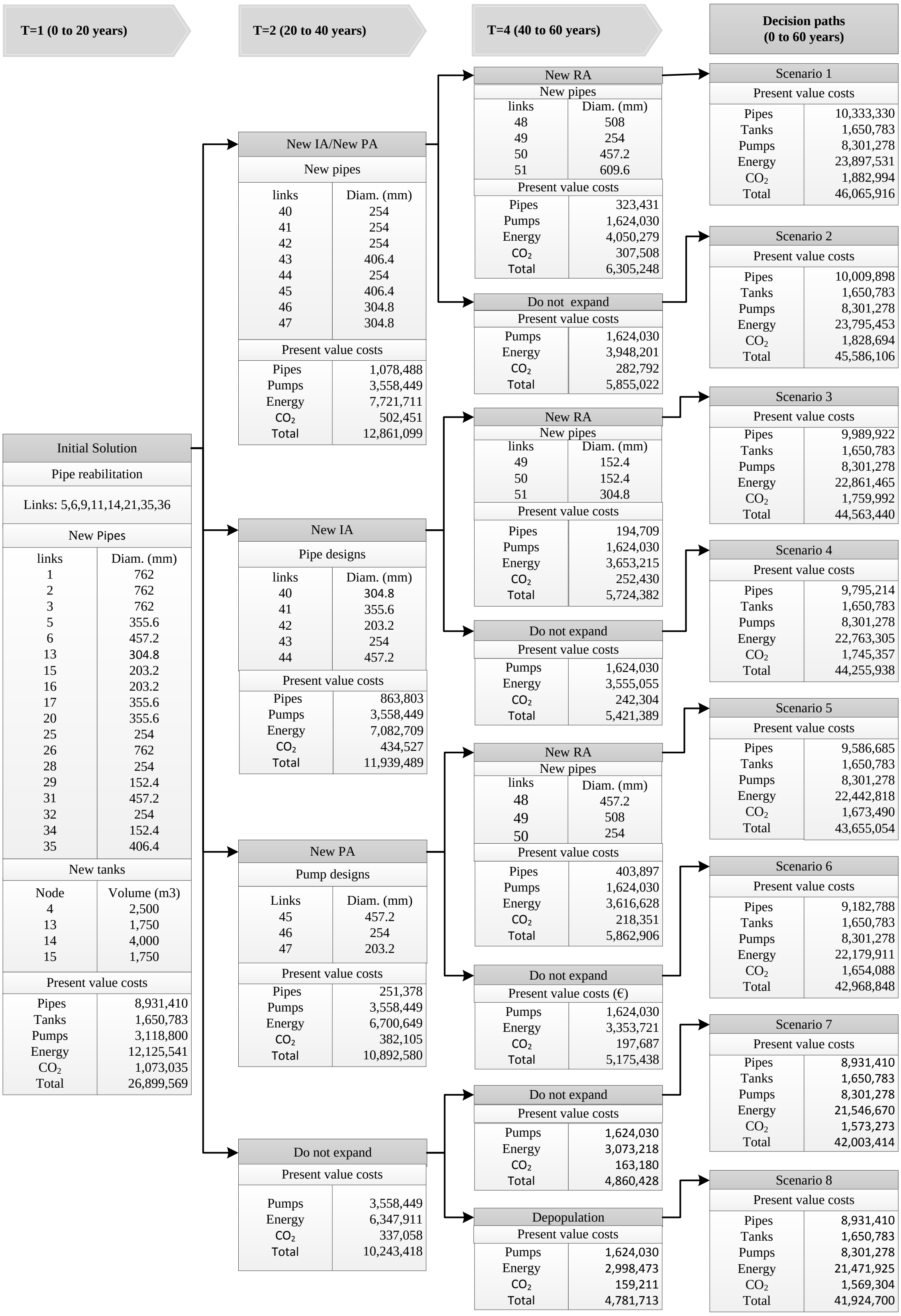

Figure 6.5: Decision tree design of Anytown network

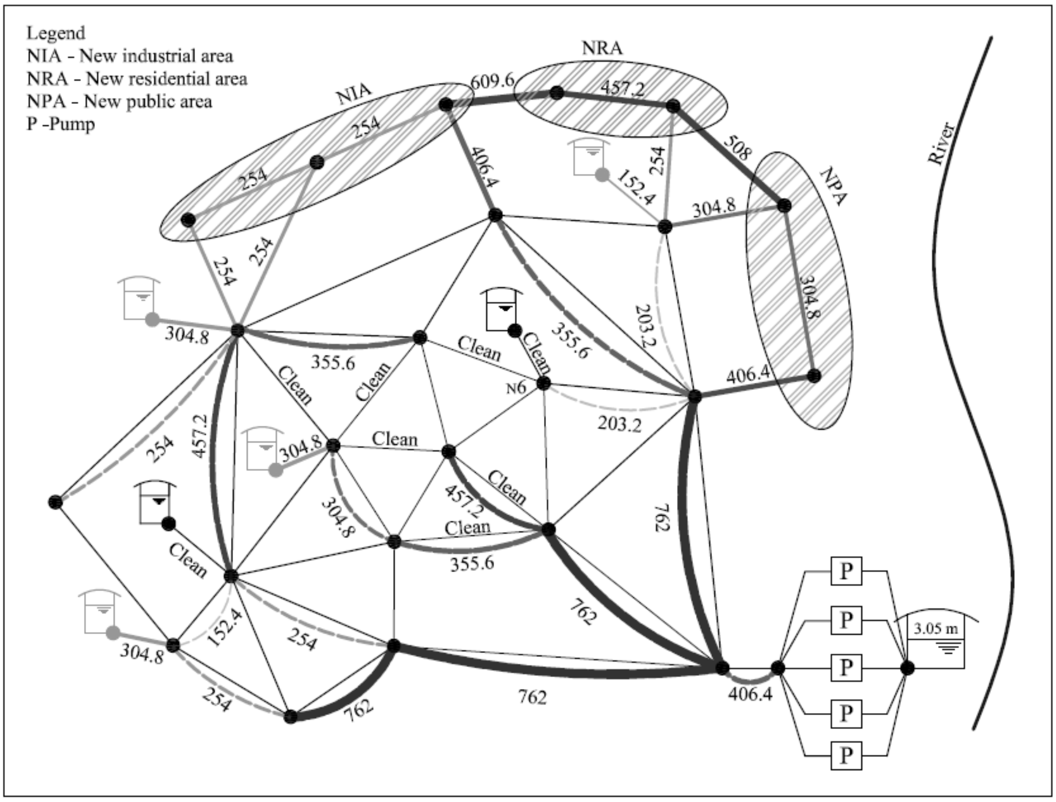

Figure 6.6: Scheme of the network for the last time interval of scenario 1

For scenario 1 the water distribution network will be expanded in the second time interval for the new industrial area and for the new public area. Furthermore the network will be expanded for the new residential area in the last time interval. Fig. 6.6 shows the pipes that will be cleaned, the diameters of the new parallel pipes and the diameters of the pipes installed in the new areas. The location of the new tanks and the inclusion of two additional parallel pumps are also shown. These interventions will result in a total life cycle cost of 46,975,016 $, including the carbon emissions costs of the constructions and operation of the water distribution network. This is the most costly solution. But if the life cycle does not follow the decision path of scenario 1, some other interventions will occur. In the case of scenario 8, it is not required for the network to expand to new areas, thus the life cycle costs is approximately 10% lower relatively to scenario 1. The ROs solution has the ability to cope with uncertainties according to the life tree and adapt the solution to new requirements.

The ROs solution for the first time interval has to be implemented at year zero. To show that considering carbon emissions in the optimization model has impact on the final solution, a comparison between the first time interval solution with and without carbon emissions costs is made. If carbon emissions costs are considered to be zero, different results are obtained. In terms of costs, table 6.9 shows some comparisons.

Table 6.9: Comparison between solutions with and without carbon emission costs

Costs	With CO_2 costs	Without CO_2 costs
Pipes	8,931,410	8,010,350
Tanks	1,650,783	1,324,100
Pumps	3,118,800	3,118,800
Energy	12,125,541	13,393,570
CO2	1,073,035	0
Total	26,899,569	25,846,820

If carbon emission costs are taken into account the total costs are high, but it can be seen that the difference is practically the carbon emission costs. However, other conclusions can also be drawn. The large part of carbon emission is due to the energy expenditure by the pumps. If carbon costs are not included, the optimization model will find solutions that have high energy costs with some reduction in terms of pipe and tank costs. From Table 6.9 it is possible to observe that maintaining the sum of the costs of pipes, tanks, pumps and energy practically the same, the consideration of carbon emissions implies allocate the costs by a different mode i.e., decreasing the pipes and tank costs and increasing energy costs. Larger diameter pipes allow reduction in the energy expenditure and with that reduce the total carbon emissions.

6.6 Conclusions

In the last few decades, the scientific community has made efforts to find tools to optimize water network design and operation. These infrastructures have high costs and are essential for the well-being of citizens. This work tries to find good solutions for water distribution networks operated under uncertain future scenarios and considering the carbon emissions costs due to installation and operation works.

This work has investigated the application of the ROs approach in search for a flexible and robust solution to a water distribution network design and operation problem considering the carbon emission costs. The problem consist in finding the minimum cost solution considering as the design variables new pipes added, cleaning and lining of existing pipes, replacement of existing pipes, siting and sizing of new tanks and installing and operating pumps. The optimization algorithm is based on simulated annealing. This method can be successfully applied to solve these problems.

The inspection of the results indicates the ROs approach is able to identify good solutions for flexible networks. The simultaneous optimization of the costs of the network and carbon emission costs achieves solutions that take into account the environmental impacts of the networks. The solution presented provides flexibility to the network and automatically minimizes the carbon emissions. The solution is obtained using the life cycle decision tree. It can be also concluded that considering carbon emissions costs permits to find solutions with practically the same investment costs, but with lower carbon emissions. This is achieved by increased investment cost and reduced energy expenditures. Nevertheless, further improvements can be achieved by considering better carbon emissions estimations as well as the comparison of the results on real networks.

Chapter 7

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

This chapter describes a multi-objective optimization model including Real Options concepts for the design and operation of water distribution networks. Real options can deal with future uncertainties over a long planning horizon. This approach is explained though a case study with some possible expansion areas defined to fit different future scenarios. A decision tree is built to outline the decision paths that can be taken during the planning horizon. 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. The model is solved by a multi-objective simulated annealing heuristic linked to a hydraulic simulator to verify the hydraulic constraints, and the results are represented as points on the Pareto front. Furthermore, one of the solutions is detailed according to the decision tree. The results achieved show that the approach can deal explicitly with conflicting objectives, with environmental impacts and with future uncertainty.

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

7.1 Introduction

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

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

This work aims to include the cost of carbon emissions in the design and operation of water networks. We must therefore quantify the emissions from the very beginning of extraction of the different materials used in the water systems until their final disposal. Dennison *et al*. (1999) use life cycle analysis to compare the environmental impact of different pipe materials. Dandy *et al*. (2006) developed a multi-objective model that uses sustainability objectives in life cycle cost analysis, energy consumption, greenhouse gas emissions and resources consumption. The tool compared the minimum cost design with the sustainable environmental design. Herstein *et al*. (2011) presents an index-based method to assess the environmental impact of water supply systems. The index aggregates the consumption of resources, environmental discharges and environmental impacts in a single index. Different materials must be used to build up the water supply infrastructure. The most common are: the steel used in pipes, accessories and pumps; reinforced concrete for tanks, manholes and moorings; plastic for pipes and accessories; aggregates for pipeline backfill and asphalt for repaving. The methodology presented in Chapter 6.4 is used to evaluate the carbon emissions involved, considering the whole life cycle including the extraction of the raw materials, and transport, manufacture, assembly, installation, disassembly, demolition and/or decomposition. The methodology also computes carbon emissions from the energy used during the network's operation. Adding together the partial contributions of pipe installation and energy consumption it is possible to compute the total carbon emissions. It is also necessary to fix a value for the carbon emissions cost for each tonne emitted. These costs are included in the optimization model presented in the next section.

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

A number of studies have developed ROs approaches to solve a variety of problems: Nembhard and Aktan (2010), who systemized applications of ROs to design and resolve engineering problems; De Neufville *et al*. (2006a) report the use of ROs in car parking problems, and Gersonius *et al*. (2010) apply ROs analysis to the option planning process in urban drainage systems to incorporate flexibility to accommodate climate change while reducing future flood risk. In the water industry, an ROs technique appears in the work of Woodward *et al*. (2011) to define maritime coastal defenses to reduce the risk of flooding. In the area of water systems expansion, Suttinon and Nasu (2010) present an ROs based approach where the demand increases. Zhang and Babovic (2012) also use a ROs approach to evaluate different water technologies in water supply systems under uncertainty. Finally, the work of Huang *et al*. (2010) describes the application of ROs to the design of water distribution networks.

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

Some benefits of flexible design are associated with the ease of accommodating different future scenarios. However, flexibility usually incurs an extra cost at the initial stage of a water network design. A flexible design is one that enables the designer, developer, or operator to actively manage or further develop the configuration of the system downstream, to adapt it to changes in the supply, demand, or economic environment. The ROs approach presented in this work uses a decision tree to reflect different scenarios that may occur during the planning horizon. The process uses a multi-objective optimization model to find solutions for the first period and for different possible future realities according to the decision tree. The model uses two objectives: a minimum cost objective function that takes into account the carbon emission costs and a level of service measure that minimizes the pressure failures that can occur over the entire planning horizon. Various scenarios are analyzed to predict different alternative future conditions.

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

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

7.2 Case study

A real options approach makes it possible to consider different adaptations over the lifetime horizon, according to urban growth. Areas can become depopulated or urbanized. These modifications have impacts on the hydraulic behavior of the networks and should be taken into account. In this section a case study demonstrating how the multi-objective model considering ROs can be employed is presented. Figure 7.1 represents a water distribution network inspired on the work of Walski *et al*. (1990). In the original case study the layout of the network is only the part represented inside the dashed line. However, in this case study it is considered the possibility to expand the network for four different areas A1, A2, A3 and A4. Furthermore it is considered an area A5 were it is possible to have a depopulated area.

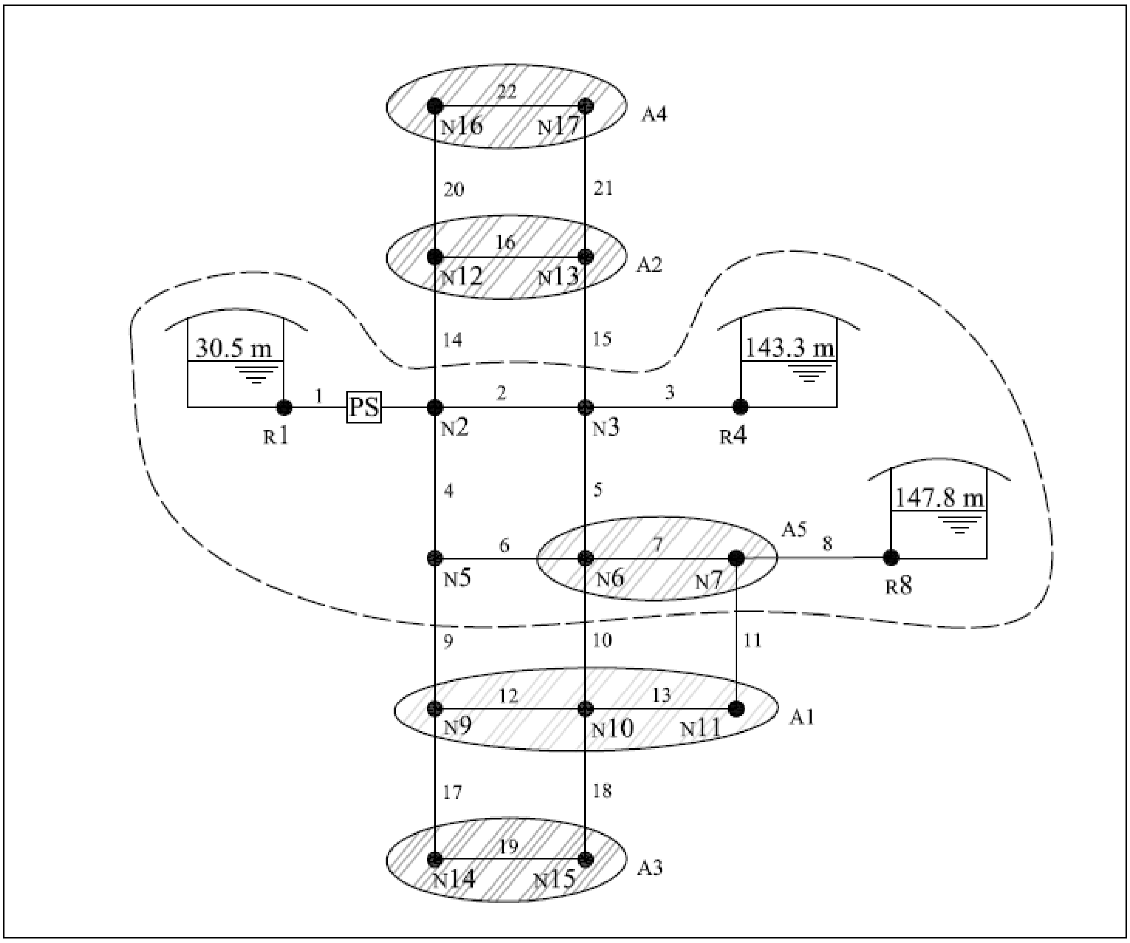

Figure 7.1: Water distribution network inspired from Walski *et al* (1990)

The network is supplied by three fixed-level reservoirs and there is a pumping station placed at link 1 to transmit energy to the flow from reservoir R1. The characteristics of the nodes for demand conditions (1) and (2) are presented in Table 7.1. This work considers two kinds of minimum pressure: the desired pressure and the admissible pressure of reference. The efficiency of the pump is 75% and the daily consumption is 20 hours at demand condition (1) with the other 4 hours at demand condition (2). The energy costs are 0.075$/KWh and should be evaluated for a 60-year period using a discount rate of 4% year. This rate was fixed based on the work of Wu *et al*. (2010).

Table 7.1: 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

This is a new network that considers the 8 different commercial diameters available for the pipe design presented in Table 7.2. Carbon emissions are computed assuming a value of 0.637 KgCO2 per each KWh of energy produced. This is a mean value of the carbon emissions of the electricity generation sector between 2005 and 2010 in Portugal (ERSE, 2012). The characteristics of the pipes are given in Table 7.3.

Table 7.2: 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

Table 7.3: 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

A planning horizon of 60 years is assumed for this case study, which was subdivided into 3 stages of 20 years. The decision tree contemplates 8 possible scenarios where different conditions can occur in future time intervals. The different decision paths that can be taken are schematized through the tree shown in Fig. 7.2.

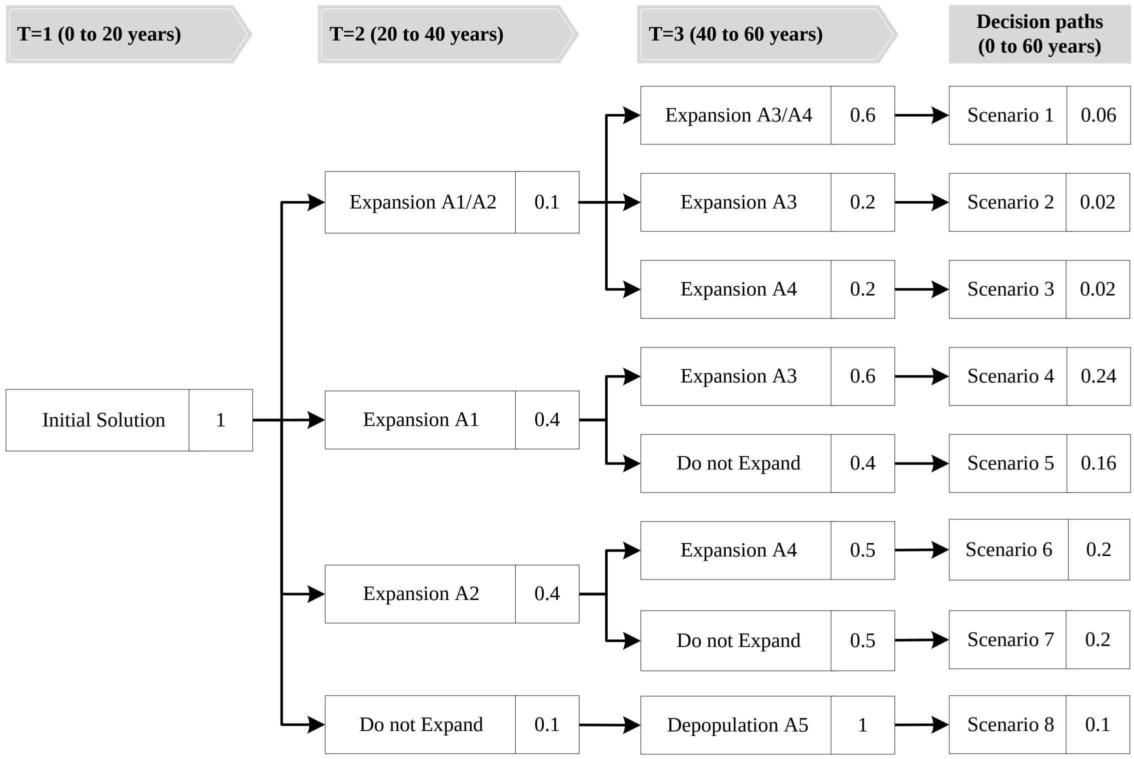

Figure 7.2: Decision tree for the planning horizon and probabilities of occurrence

Each decision path has different probabilities. For this case study the probabilities considered for the different decision nodes are shown in the square boxes of Fig. 7.2. For real case studies, these probabilities have to be defined by decision makers using appropriate methods and knowledge. The values shown in the last branches of the decision tree are the probabilities of the scenarios and are calculated by multiplying the probabilities of all nodes on the path of that scenario. For the first period T=1 an initial design for the network is defined. For T=2, four different situations can occur, expansion to A1 and A2, expansion to A1, expansion to A2 and no expansion. In the last period T=3, new expansion areas are possible, A3 and A4, expansion to A3, expansion to A4 and no expansion. It is also possible to have a depopulated area A5 where the consumption could decrease by 30%. These scenarios, included in the decision tree of Fig. 7.2, are deemed the most probable future conditions for the case study.

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

7.3 Optimization model

This work presents a multi-objective model with two conflicting objectives. One of the objectives consists in minimizing the costs of construction and operations of the network. These systems are responsible for important carbon emissions during construction but mostly during the operation phase. Therefore, the carbon emissions are also computed to try to achieve an environmental friendly design for the water distribution system. The other objective of the model is used to determine a solution taking into account the level of service. As it was stated, the model considers two kinds of minimum pressures, the minimum desirable pressures and the minimum admissible pressures. If nodal pressure remain between these two limits, the pressure violations are summed for all nodes. However the model considers that the network has to obey the desirable pressure constraints for the first 20 years. In the subsequent time intervals, pressures can decrease until admissible pressures, according to the probability of occurrence of the decision paths.

The decision model aims to minimize two objectives. The first one is given by Eq. 7.1.

$$OF1 = Min\ \left(Ci + Cf\right) \tag{7.1}$$

Where:

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

Cf – future costs (\$).

The objective function *OF1* of Eq. 7.1 is written so that the solution for the first period, T=1, can be determined while taking into account the different decision paths of the planning horizon. The objective function seeks to minimize both the initial cost and the probable future cost of the system. The term *Ci* computes the cost of the network for the first period T=1 of planning and is given by Eq. 7.2.

$$Ci = \left(\sum_{i=1}^{NPI} \left(Cpipe_{i,1} + CCEpipe_{i,1} \right) + \sum_{j=1}^{NPU} \left(Cps_{j,1} \right) + \sum_{d=1}^{NDC} \left(Ce_{d,1} + CCEe_{d,1} \right) \right) \tag{7.2}$$

Where:

NPI - number of pipes in the network;

$Cpipe_{i,1}$ - cost of pipe i in period $T=1$;

$CCEpipe_{i,1}$ - cost of the carbon emissions of pipe i in period $T=1$;

NPU - number of pumps in the network;

$Cps_{j,1}$ - pumping station costs of pump j in the period $T=1$;

NDC - number of demand conditions considered for the design;

$Ce_{d,1,}$ – present value cost of energy in demand condition d in period $T=1$;

$CCEe_{d,1,}$ – present value cost carbon emissions by energy in demand condition d in period $T=1$.

The initial cost is given by the sum of the cost of pipes, the cost of pumps and the present value of energy cost. The carbon emissions’ cost of pipes and energy are also included. The carbon emissions related to other network elements as pumps are not considered, since they are neglected compared with pipe construction and energy. The other term of the objective function *OF1* represents the future cost of all the scenarios (Eq. 7.3), weighted by the corresponding probability of each scenario.

$$Cf = \sum_{s=1}^{NS} \sum_{t=2}^{NTI} \left(Cfuture_{t,s} \cdot \prod_{nt=2}^{t} prob_{nt,s} \right) \tag{7.3}$$

Where:

NS - number of scenarios;

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

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

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

The future scenarios' costs are arrived at by summing all possible future costs, starting from T=2. These costs are computed by multiplying the cost of each decision option by the probability of taking that decision path. A mean is obtained for the future possible costs for the network. The term $Cfuture_{t,s}$ is computed in Eq. 7.4, for all periods beginning in $T=2$ (the costs for the first period are already calculated in the *Cinitial* term), and it is given by the sum of three terms.

$$Cfuture_{t,s} = \begin{pmatrix} \sum_{i=1}^{NPI} \left(Cpipe_{i,t} + CCEpipe_{i,t} \right) + \\ + \sum_{j=1}^{NPU} \left(Cps_{j,t,s} \right) + \sum_{d=1}^{NDC} \left(Ce_{d,t} + CCEe_{d,t} \right) \end{pmatrix} \cdot \frac{1}{\left(1+IR\right)^{Y_t}} \tag{7.4}$$

Where:

NPI - number of pipes in the network;

$Cpipe_{i,t}$ - cost of pipe i installed in period t;

$CCEpipe_{i,t}$ - cost of the carbon emissions of pipe i installed in period t;

NPU - number of pumps in the network;

$Cps_{j,t}$ - pumping station costs of pump j installed in period t;

NDC - number of demand conditions considered for design;

$Ce_{d,t}$ – present value cost of energy (actualized for the first year of the time interval t) in demand condition d for period t;

$CCEe_{d,t}$ – present value cost carbon emissions by energy (actualized for the first year of the time interval t) in demand condition d for period t;

IR - annual interest rate for updating cost;

Y_t - year when costs will be incurred for period t.

The first term of Eq. 7.4 computes the cost of pipes and carbon emissions costs to be installed for different decision paths, the second term computes the costs to install pumps every 20 years and finally the last term computes the cost of energy and the carbon emission costs associated with energy consumption. Thereafter, the present value costs are computed, considering the year when costs will be incurred.

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

The second objective function is given in (7.5). The aim of this expression is to minimize the total pressure violations for the different future scenarios.

$$OF2 = Min\ (TPV) \tag{7.5}$$

Where:

TPV - total pressure violations (m).

The multi-objective model determines different solutions for different levels of pressure violations. The total pressure violations are computed according to Eq. 7.6:

$$TPV = \sum_{s=1}^{NS} \sum_{t=2}^{NTI} \sum_{d=1}^{NDC} \sum_{n=1}^{NN} Max\left\{0;\left(Pdes_{\min,n,d} - P_{n,d,t,s}\right)\right\} \tag{7.6}$$

Where:

NN - number of nodes;

$Pdes_{min,n,d}$ - minimum desirable pressure at node n for demand condition d;

$P_{n,d,t,s}$ - pressure at node n at demand condition d for time interval t and in scenario s.

Eq. 7.6 computes the sum of pressure violations for each scenario, each time interval (starting from T=2), each demand condition and each network node. This sum of pressure violations can be used as a measure of the network performance during the entire planning horizon.

Table 7.1 presents the desirable and admissible minimum pressures for each node. However these admissible pressures are a threshold limit to compute the lowest value that the nodal pressures can reach according to the probability of scenarios. The constraint presented in expression (7.7) aims to obtain higher values, and thus less pressure violations, for scenarios with high probabilities of occurrence.

$$P_{n,d,t,s} \geq \left\{ \prod_{nt=2}^{t} prob_{nt,s} \left(Pdes_{\min,n,d} - Padm_{\min,n,d} \right) + Padm_{\min,n,d} \right\}$$
$$\forall n \in NN; \forall d \in NDC; \forall nt \in NTI; \forall s \in NS \tag{7.7}$$

Where:

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

Expression (7.7) is just one of the constraints of the model. Other constraints of the model are those normally used in the optimal design and operation of water distribution systems (Cunha and Sousa, 2001).

7.4 Optimization tool

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

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

This method makes use of an archive where the non-dominated solutions seen so far are stored. The structure of the proposed optimization tool is presented in Fig 7.3.

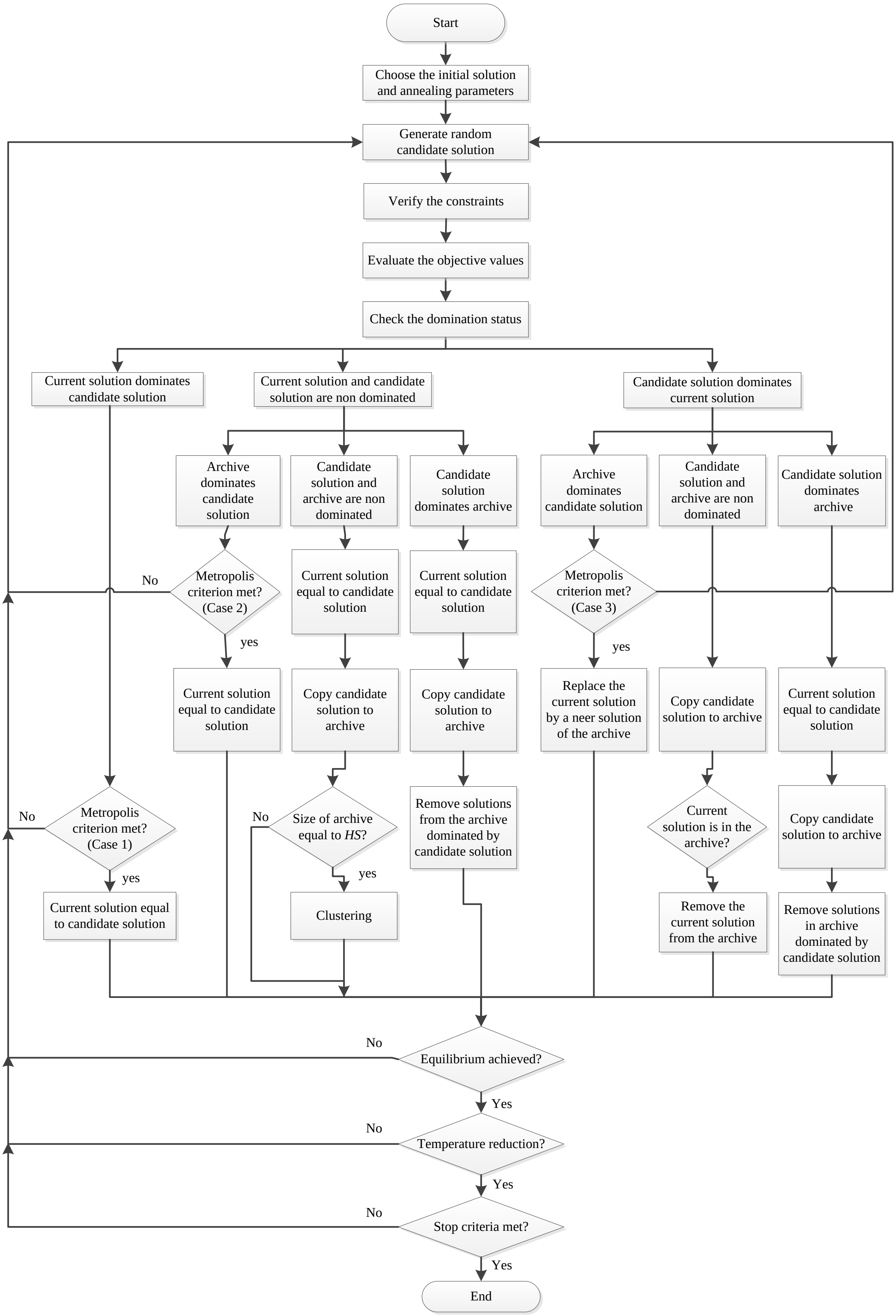

Figure 7.3: Multi-objective simulated annealing flow chart

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

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

The dominance between two solutions is computed by Eq. 7.8:

$$\Delta dom_{a,b} = \prod_{i=1, OF_i(a) \neq OF_i(b)}^{N} \left| OF_i(a) - OF_i(b) \right| \tag{7.8}$$

Where:

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

N– total number of objectives;

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

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

The dominance between two solutions is computed by multiplying the difference in the values of the *N* objectives, if this difference is other than zero. The domination concept is explained in Fig. 7.4 for the example of two objective functions.

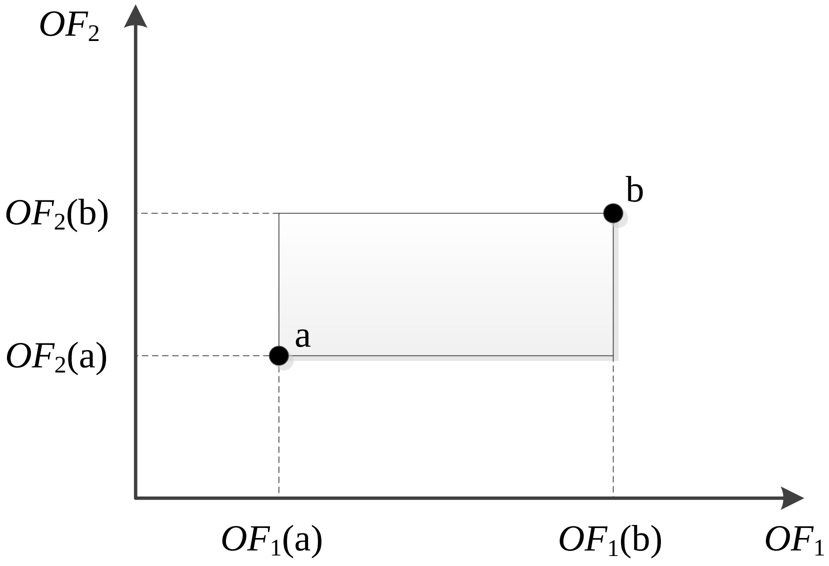

Figure 7.4: Domination between solutions *a* and *b*, adapted from Bandyopadhyay *et al*. (2008)

The amount of domination is represented in Fig. 7.4 by the area of the rectangle between solutions *a* and *b* and is used by the multi-objective simulated annealing to compute the acceptance probability.

Three different conditions can occur when checking the domination status: current solution dominates candidate solution; candidate and current solutions are non-dominated and candidate solution dominates current solution. According to the domination status, it can also be necessary to compute the dominance of the candidate solution in relation to the solution in the archive. According to the situation, the solution can be accepted directly and become the new current solution. But, if the candidate solution is dominated by current solution or by the archive, a metropolis criterion is used to compute the acceptance probability for three distinct cases of dominance, as presented in Fig. 7.3. For case 1, the dominance is computed by Eq. 7.9:

$$\Delta dom_{mean} = \frac{\left(\sum_{i=1}^{p} \Delta dom_{i,cand}\right) + \Delta dom_{curr,cand}}{p+1} \tag{7.9}$$

Where:

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

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

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

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

Eq. 7.9 considers not only the dominance of the current solution in relation to the candidate solution, but also the sum of dominance of all the solutions in the archive that dominate the candidate solution. This sum is divided by the number of solutions in the archive that dominate the candidate solution, plus one, to take into account the dominance of the current solution relative to the candidate solution. For case 2, the current and candidate solutions are non-dominated and the mean dominance is computed by Eq. 7.10:

$$\Delta dom_{mean} = \frac{\left(\sum_{i=1}^{p} \Delta dom_{i,cand}\right)}{p} \tag{7.10}$$

This expression is analogous to case 1, except that now the dominance between the current and candidate solutions is not taken into account. Lastly, for case 3, the candidate solution dominates the current solution. But if the archive dominates the candidate solution a minimum dominance is computed through Eq. 7.11, deemed equal to the minimum value of dominance between the solutions of the archive that dominate the candidate solution.

$$\Delta dom_{\min} = Min(\Delta dom_{i,cand}, i = 1,...p) \tag{7.11}$$

Where:

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

After calculating the dominance in these three different cases the Metropolis criterion is used to compute the acceptance probability of the candidate solution. For cases 1 and 2 the acceptance probability is computed by Eq. 7.12, and for case 3 the acceptance probability is computed by Eq. 7.13:

$$P_{acp} = \exp\left(\frac{-\Delta dom_{mean}}{T}\right) \tag{7.12}$$

$$P_{acp} = \exp\left(\frac{-\Delta dom_{\min}}{T}\right) \tag{7.13}$$

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

According to the structure of the algorithm of Fig. 7.3, the multi-objective process is repeated for a number of iterations at each temperature. The temperature is reduced until the stop criteria are attained and the process stops.

The archive contains the non-dominated solutions found so far. The size of the archive is given by two limits, a lower limit *LL* and an upper limit *SL*. During the search process, solutions are stored in the archive until it is completed with *SL* solutions. Then a clustering technique is used to lower the number of solutions stored to the lower limit *LL*. The clustering technique is based on the work of Hartigan and Wong (1979). This tool aims to find a small number of *LL* solutions that represents the group of *SL* solutions. The values are *LL*=30 and *SL*=10 and are defined according to the number of final of Pareto front solutions that we wish to obtain.

This optimization method was linked to the EPANET Rossman (2000) hydraulic simulator to verify the hydraulic constraints of the multi-objective model.

7.5 Results

Figure 7.5 provides some results obtained by solving the multi-objective model given by the objective functions (Eq. 7.1 and Eq. 7.5) and considering the constraints. The model determines the Pareto front consisting of 10 different solutions. The total cost represents not only the investment and operation costs but also the carbon emission costs of the network lifecycle. The minimum pressure violations are arrived at by summing all the violation values for each node and considering the different conditions that the network can cope with.

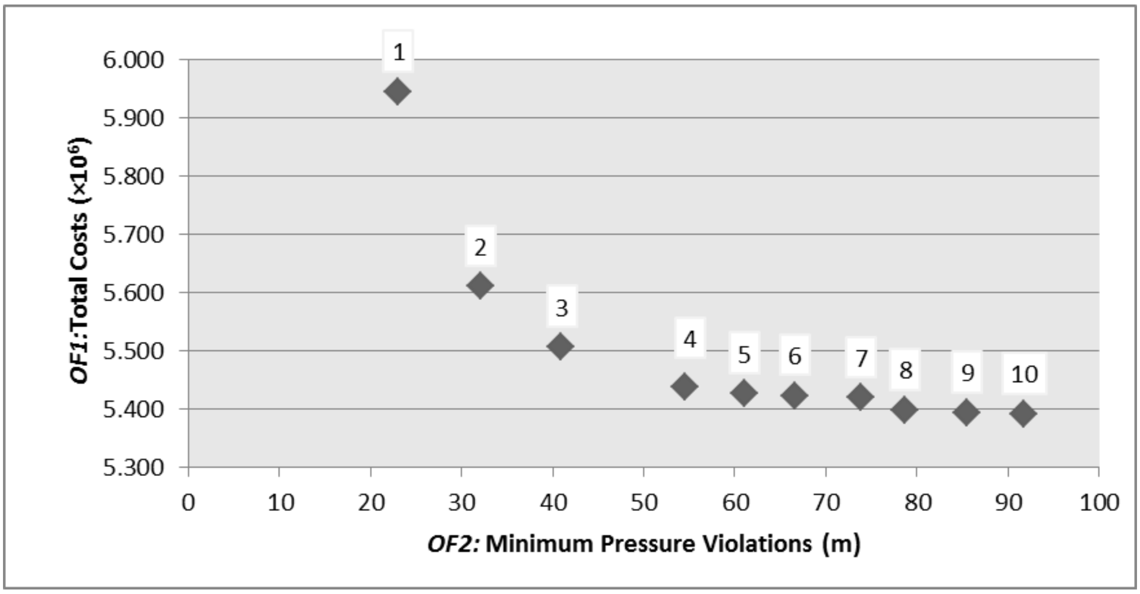

Figure 7.5: Pareto front of objectives *OF1* and *OF2*

The Pareto front that can be traced through the points represented in Fig. 7.5 gives an idea about how the cost decreases when pressure violations are permitted. 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. 7.4.

Table 7.4: 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

Table 7.4 also shows that the total cost falls if high pressure violations are allowed. A higher level of service requires an increase in the network capacity to meet the minimum desirable pressures of the network. We can also see that for solutions 10 to 4 a small increment in the total cost makes it possible to define solutions with significant falls in the total minimum pressure violations. Thus, it is possible to improve the level of service of the network within this range of solutions for a low expenditure.

The carbon emission cost falls as the PPE cost decreases, as indicated in Table 7.4. The carbon emission varies for different solutions on the Pareto front between a minimum of $146,227 for solution 10 and a maximum of $161,019 for solution 1. In fact, the variation in carbon costs for these 10 solutions is small and thus the impact on the optimization process is low. This value is nonetheless included in the model to quantify the carbon emissions involved in construction and operation of water networks.

In order to explain the way how solutions are defined, the extremities of the Pareto front (solution 1 and solution 10) will be detailed next, just for the first scenario..

Fig 7.6 shows the total cost of the solution 1, for scenario 1 and for the 60-year planning horizon, is $7,455,992 and is composed of PPE costs of $7,260,067 and carbon emission costs of $195,925, associated with the design and operation of the network. The total cost of solution 10 (Fig. 7.7) for the same scenario and for the 60-year planning horizon, is $7,068,095 and consists of PPE costs of $6,883,401 and carbon emission costs of $184,694. In this scenario all the areas are expanded, thus the total consumption in the network increases. This is the most demanding case considered in the decision tree and has a 6% probability of occurrence. The diameters are given in millimeters and the expansion areas are indicated by traced ellipses aggregating the new consumption nodes.

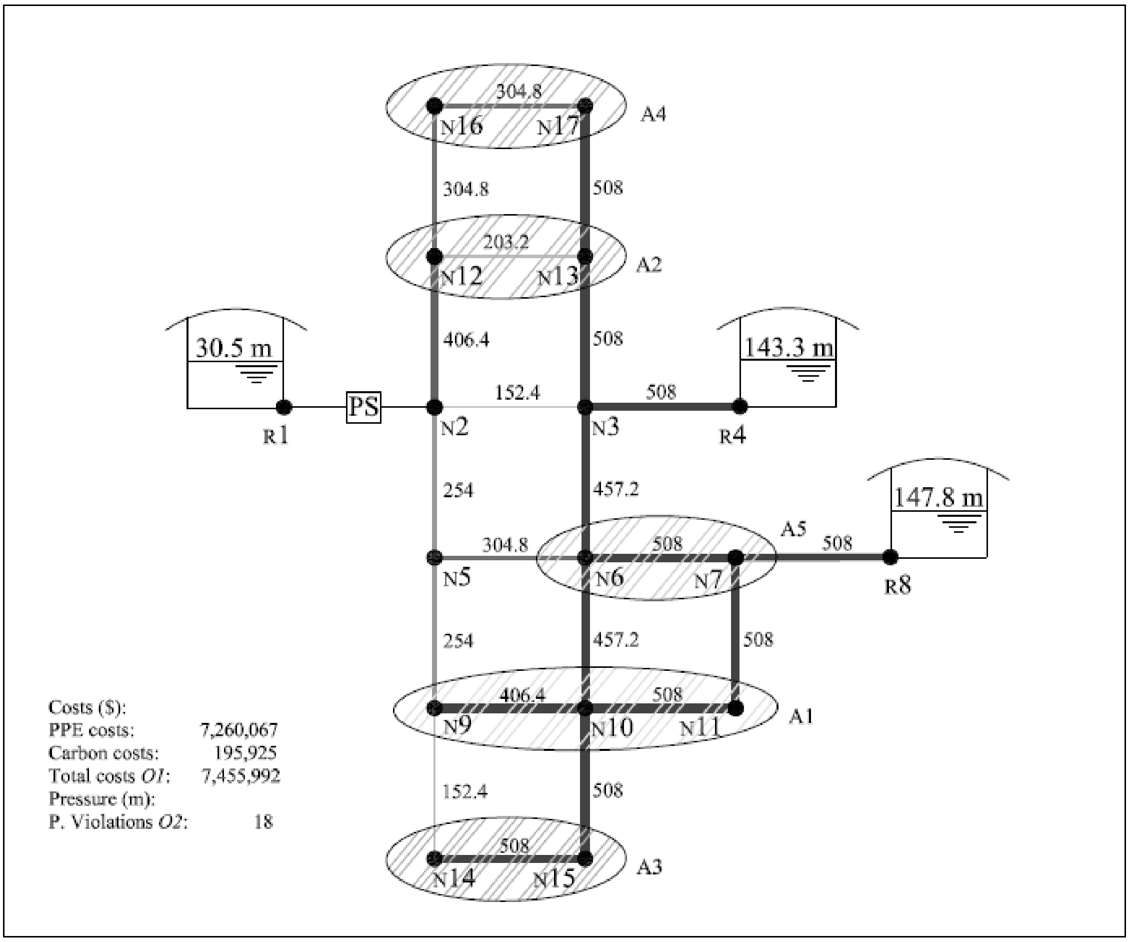

Figure 7.6: Design for solution 1 and considering scenario 1 in the last time interval

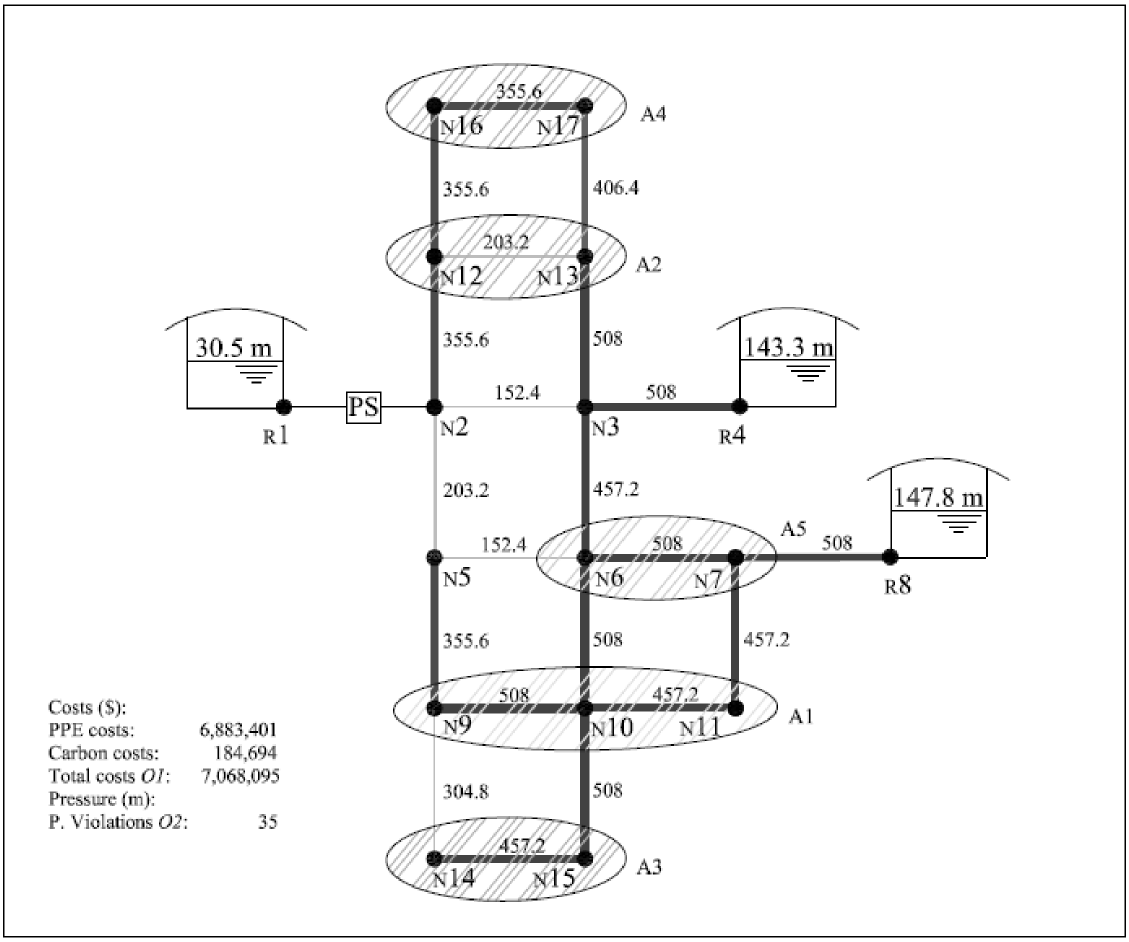

Figure 7.7: Design for solution 10 and considering scenario 1 for the last time interval

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

The optimization model aims to simultaneously minimize the installation, operation and carbon emission costs of the first objective function *OF1*. But it also aims to minimize the pressure violations given by objective function *OF2*. The designs represented by Figs 7.6 and 7.7 can be used as solutions for the case study described in this work if scenario 1 occurs. However, other solutions given by the multi-objective model can be chosen, according to the preferences of decision makers. All the possible decision paths of solution 1 of the Pareto front in Fig. 7.5 determined by the multi-objective tool, are shown in greater detail in Fig. 7.8.

Decisions have to be made for each time interval of the decision tree. Fig. 7.8 presents, for each node, a table with the results of design solution 1 of the Pareto front, beginning with the diameters of pipes (in millimeters) required in the network. Then the costs are shown, divided into PPE costs, carbon costs, total cost and minimum pressure violations. Finally, the last branches of the decision tree represent the total cost of PPE, carbon emissions, total cost and total pressure violations for each scenario. These figures represent, for each scenario, the total cost and pressure violations that may be expected if that scenario occurs.

Only the first stage design decision has to be implemented now, and therefore the future decisions will be made as new information comes. The ROs approach is formulated as a multi-stage model whose objective is to design the network for the first time interval and help decision makers to find the best system development strategy while minimizing the costs.

The design for the network depends not only on the hydraulic conditions of the present decision but on the decision paths that can be followed, too. The decisions taken in prior stages have to accommodate the future possible conditions of the network. The ROs approach considers different scenarios with different probabilities. By adding together the initial cost and all the future weighted costs we can arrive at the present value of the ROs solution in the Pareto front, which is $\$5.945\times10^6$. The sum of all pressure violations at the nodes of the network for this solution is 23m.

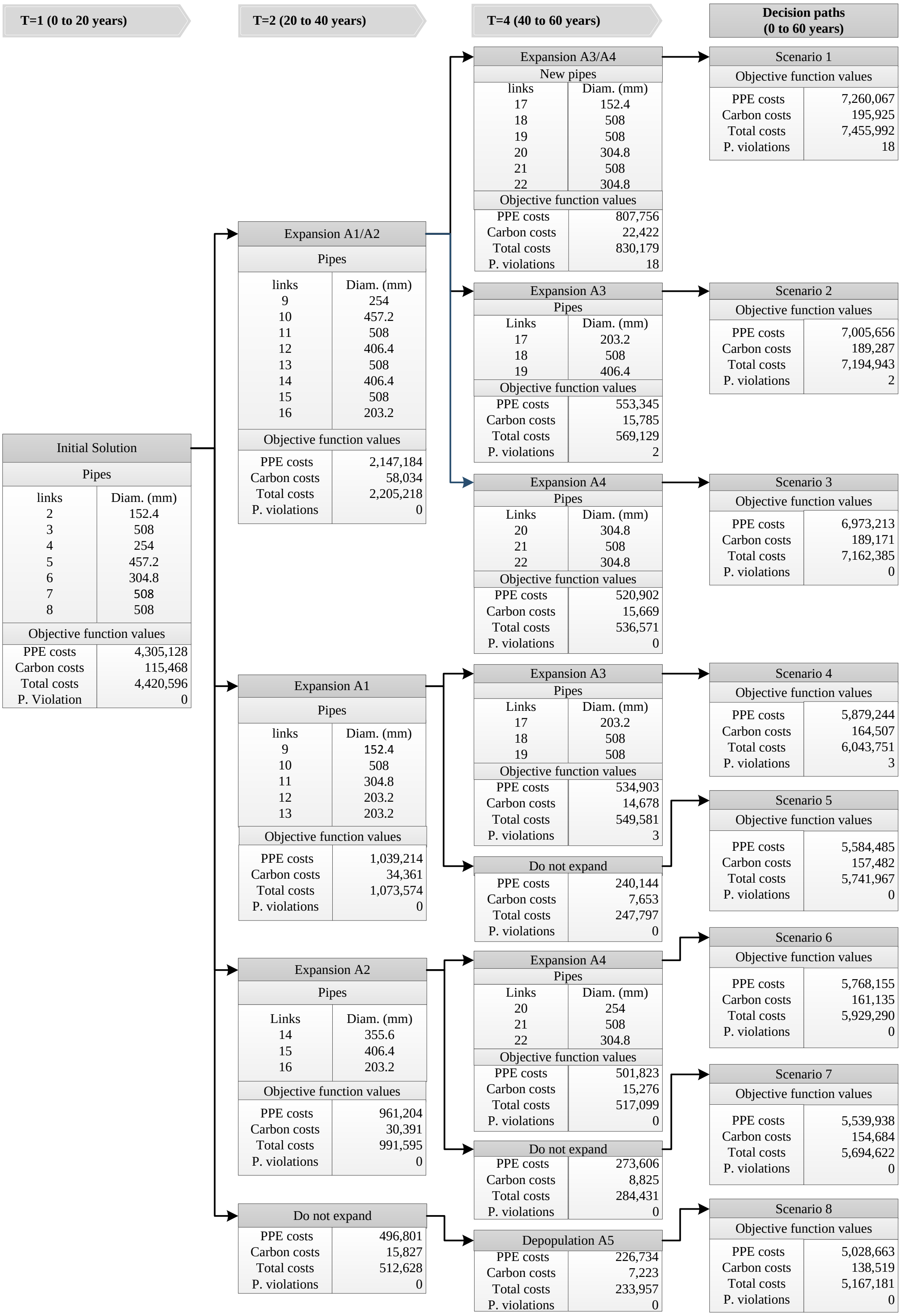

Figure 7.8: Designs for solution 1 according to the planning horizon decision tree

The design achieved for each link has enough capacity to extend the network to future new areas that may be built. Pipes 2 to 8 (see Fig. 7.1) are designed in the first stage, but need to have enough capacity for different decision paths. However, there is a tradeoff to determine the minimum cost solution involving carbon emissions and the minimum pressure violations that are allowed in the planning horizon.

7.6 conclusions

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

The model aims to minimize two objectives. The first is given by the total cost computed as the sum of the installation cost of pipes and pumps plus the energy costs and the carbon cost over the lifecycle of the network. These costs are actualized to year zero and weighted by the probabilities of the future scenarios. The second objective is to minimize the minimum desirable pressure violations computed by summing the extent of the violation for all the nodes of the network and for all the scenarios. This objective can be seen as a quality level of service for the water supply system. The model is solved by a multi-objective simulated annealing heuristic and the results are represented as points on the Pareto front. Carbon emissions are considered in the model. These environmental impacts are reduced by decreasing the size of the diameters and by cutting energy consumption. But, in this case study, there is a relationship between the pipe design and the energy consumed by pumps at link 1. Energy consumption can be reduced by using large pipe diameters that decrease the head losses, thereby reducing the amount of energy required to pump water. The optimization model has to handle this tradeoff.

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

From the results, it was concluded that the carbon emission costs do not have a significant influence on the objective function value. As a future trend, carbon emission costs should be included explicitly in the multi-objective optimization model to express the compromise between the minimization of these eco-friendly aspects and the other objectives.

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

Chapter 8

Conclusions and Future Trends

The main objective of this study is to develop a decision-aid tool for the optimal design and operation of water distribution networks capable of dealing with uncertainty and finding more robust and reliable solutions. Given this, the proposed approaches are discussed in this chapter. The capabilities of and conclusions from the application of these tools, as well as some possible future trends, are described.

Keywords: robust design, real options, simulated annealing, carbon emissions, decision-aid tool.

This work addresses the robust design and operation of water distribution networks. These systems are essential for people's wellbeing and their careful planning is essential. The main contribution of this thesis is the development of a set of optimization tools to help decision makers with the technical support of their decisions, taking into account economic and environmental impacts and uncertainty aspects related to the water supply systems. Four main decision models were developed:

- A robust optimization model that handles different levels of reliability (chapter 4).
- A decision model based on a real options approach (chapter 5).

- A decision model based on a real options approach and taking environmental impacts into account (chapter 6).
- A multi-objective decision model based on a real options approach (chapter 7), including the contributions of chapters 4, 5 and 6 by explicitly considering: the level of reliability of chapter 4; the uncertainty represented by the decision trees of chapters 5 and 6 and the environmental impacts detailed in chapter 6.

These models were solved by developing two optimization methods: a single-objective optimization algorithm based on a simulated annealing heuristic to solve the models of chapters 4, 5 and 6; and a multi-objective optimization method, also based on simulated annealing, to solve the model of chapter 7. Moreover, regarding chapters 6 and 7, a methodology to compute the environmental impacts of water distribution networks was established. The conclusions that can be drawn from the application of these decision-aid tools are now described.

Chapter 4 presented a robust optimization model to help decision makers reach a good compromise between robustness and cost. The application of this approach was demonstrated by means of two case studies. Robustness was assured by two different strategies and the results were compared. These strategies involved either reinforcing the network by increasing the pipe diameters or designing the pipes for normal operating conditions and introducing a pumping station to deal with the extreme operating conditions. Results showed that introducing a pumping station can be less expensive if a highly reliable design is required. It must also be pointed out that the strategy of overdesigning pipes leads to low velocities and high water residence times. The use of a pumping station can also be viewed as an alternative for existing water supply systems. Strengthening the infrastructure links may be difficult for some system, especially if it involves construction in urban areas, and it could also be too expensive. So alternative strategies should be used.

In chapter 5, the real options approach was introduced in a decision making process under uncertainty, in the field of water supply network design. Furthermore, this approach is justified. The optimization model set out in this chapter minimizes the financial costs over the whole planning horizon, which is divided according to a decision tree. A specific case study was used to better explain the application of real options. A number of alternatives were considered for the infrastructure by dividing the planning horizon into periods, with the aim of making mid-course corrections or additional investments. Some comparisons were also made. The differences in cost between the real options solution and the solutions for each scenario computed individually were discussed. Furthermore, the flexible design provided by real options was compared with the traditional design for the same case study. Results showed that the flexible design given by the real options made savings possible if an extended and uncertain planning horizon analysis is performed. However, in the case study, an adaptable design required an extra initial cost for the first 20 years since the flexible solution is more costly than the solution achieved by a traditional design, which does not take future uncertainty into account. Traditional designs will not be sufficiently robust to accommodate the future scenarios and thus some pipes in the network will need to be reinforced. These reinforcements will increase the total cost of the system over the entire planning horizon. Real options lead to better results than the traditional design because it allows short-term upgrades to be implemented. Furthermore, flexible solutions always give decision makers the chance to recalibrate the network when the real development is considerably different from the conditions initially assumed.

In chapter 5, the real options approach was used to solve a simple water network design. Chapter 6 proposes a similar optimization model based on real options, but it is extended to include the environmental impacts of a complex case study. The problem consisted of finding design variables, specifically by adding new pipes, cleaning and lining existing pipes, replacing existing pipes, siting and sizing new tanks and installing and operating pumps. The solution was obtained by using the simulated annealing optimization algorithm. The simultaneous optimization of the financial costs and environmental costs was included in the objective function of the model.

The environmental impacts were obtained by a methodology that defines and computes the quantities of materials and energy used in water supply systems, and uses that to compute the carbon emission costs associated with the construction and operation of the network. The achieved solutions provide flexible intervention strategies for the network and automatically minimize the carbon emissions. For the case study, the large part of carbon emissions derived from energy consumed by the pumping station. In fact, when carbon emission costs are taken into account the total cost of the network increased. It can also be noted that this difference in costs is approximately equal to the increase in the carbon emission costs. Furthermore, when carbon costs are excluded, the solution found by the optimization model had high energy costs and low construction costs for pipes and tanks compared with the solution that included the carbon costs. Thus, the approach can maintain the total cost of pipes, tanks, pumps and energy and reduce the carbon emissions. Selecting large pipes results in a reduction in energy expenditure by pumps. Furthermore, the total carbon emission is also reduced with practically no impact on the total cost.

Chapter 7 presented a real options approach that includes the contributions given by the last three models in a single approach. It deals explicitly with conflicting objectives through the multi-objective optimization tool described in chapter 3.4. A case study with possible expansion areas was defined according to different future intervention strategies. This chapter described a real options approach that takes future uncertainty into account and deals with conflicting objectives over a long-term planning horizon. The optimization model resulted in solutions to be implemented for all the nodes of the decision tree.

The model aimed to minimize two objectives. The first objective was to compute the total cost, comprising the cost of pipes and pumps, the energy costs and the carbon emission costs for the entire life cycle of the infrastructure. The second objective was to minimize the pressure violations. This objective function is computed by summing the extent of pressure value that is below a threshold limit, for all the nodes of the network, for all the demand situations and for all the scenarios.

Carbon emissions are also addressed in the model. The results show that the carbon costs of the case study can be cut by decreasing the pipe diameters and by reducing the energy consumption of pumps. However, there was a relationship between pipe design and energy expenditure and the optimization model had to deal with this tradeoff.

The model was solved by a multi-objective simulated annealing heuristic and the results were represented as a Pareto front. One of the solutions on the Pareto front was presented in detail according to the intervention strategies in a decision tree. The solution shows the values for the decision variables plus the total investment amount, the operating and carbon emission cost of the first objective function and the total minimum pressure violations of the second objective function. The results also suggest that a multi-objective simulated annealing method can be successfully used for these problems, resulting in Pareto front solutions.

This thesis also makes other contributions of use to constructing decision-aid tools. A new real options analysis based approach for representing and evaluating different intervention strategies on water distributions networks considering future uncertainty is one such contribution. Decision trees make it possible to apply real options and to adapt the solution to different future situations. This approach enables decision makers to look for possible options and understand the impact of choosing a specific decision path. The incorporation of flexibility provided by a real options approach can reduce the amounts of the various resources used over the planning horizon of water distribution networks. Chapters 5, 6 and 7 make use of this approach.

In the optimization field, two tools were developed. A single-objective method based on simulated annealing heuristic that was formulated and improved by using tabu lists to avoid cycles in the search. This optimization tool is described in chapter 3.3 and is used to solve the optimization models described in chapters 4, 5 and 6. The second tool is a multi-objective simulated annealing optimization method. This method presents the concept of Pareto-dominance and makes use of an archive where the non-dominated solutions are stored. At the end of the search process, the archive contains the final non-dominated solutions that can be used to examine the Pareto frontier of the problem. This optimization tool is described in chapter 3.4 and is used for the optimal design of water supply systems involving the conflicting objectives in chapter 7.

Furthermore, incorporate environmental impacts were incorporated into the decision support tools by means of a procedure to compute carbon emission costs. Carbon emissions were dealt with by quantifying the embodied energy from the very beginning of the extraction of the different materials used for water networks until their final disposal. The embodied energy is computed as the sum of the total energy expended during the entire life cycle of the product. The quantities of materials used to install pipes and construct tanks were computed. Also, the electricity used during the water infrastructure operation produces significant carbon emissions, which should be taken into account. As a result, this methodology can find the total amount of energy required to construct and operate a water distribution network. It is then possible to compute the carbon emission costs for the entire planning horizon of the infrastructure. These costs can be incorporated in the decision model to obtain environmentally friendly intervention strategies for sustainable planning.

The research works described in this thesis can be used separately or as blocks of an integrated decision support tool to be applied throughout the horizon planning scheme. Chapter 7 combines some works of this thesis in a single decision-aid tool. The multi-objective tool proposed in chapter 7 offers advantages to the decision making process because a range of conflicting objectives can be optimized simultaneously, thus resulting in a tradeoff of solutions. These methods can provide decision makers with a range of Pareto optimal front solutions containing the essential information for taking decisions.

In future developments of this work, the question of water quality can be added to the decision models. Design and operation practices have a high impact on flow directions, flow velocity and water age. Thus, water quality could be taken into account to ensure that solutions satisfy water quality requirements.

The results determined by the models developed were illustrated through several case studies to demonstrate the application and the potential usefulness of these decision tools. In chapter 6 the case study is based on a complex network. This illustrates the ability of the optimization method to solve these problems and supports the idea that its application to real cases is viable. However, in the future these approaches will be implemented in real-world case studies to demonstrate their practical application.

The application of these decision tools is flexible in relation to the type of cost functions associated with the different elements of water distribution networks. However, further work should be carried out to define the cost of these elements more accurately in real world case studies. Such costs depend on a number of issues and are subject to important market and temporal variations. Nevertheless, cost functions presented in this thesis could be further improved.

Regarding environmental impacts, the methodology used to compute carbon emissions was developed using a number of simplifications. The quantities of materials used during construction were computed based on further simplifications. For example, to determine the embodied energy of pipe construction we must calculate the quantity of aggregates, and in this work they are assumed to be only a function of the commercial pipe diameter. The width of the trench is assumed to be to the same as the external diameter of the pipes plus 0.5 m. The walls of the trench are taken to be vertical and the entire trench is filled with aggregates. These computations are a rough approximation of real pipe installations. Additionally, tank construction materials are defined based on walls and slabs having the same thickness, regardless of the volume of the tank. This is also a rough approximation that can be enhanced. However, it should be pointed out that the models can easily include other ways to compute the embodied energy of materials used in network construction.

Uncertainty is modeled by real options through decision trees where different future paths can be followed during the planning horizon. These decision path scenarios were defined according to certain probable and important alterations in the system. The expansion of the network to new areas and changes in demand were considered in this thesis. However, other options can be included as well. Features such as the addition of new sources of water in some locations of the network and other options typical of real-world water distribution networks can be used.

Extra objective functions could be included in the decision models. It is important to define ways to include social and business aspirations in the objective functions. Other objectives of the decision model can be given by minimizing the total amount of energy expended during construction (embodied energy of materials) and during operation, mainly by pumping stations (electric energy), with the aim of reducing the total carbon emissions. Environmental impacts could also be explicitly considered in multi-objective optimization models with the purpose of determining the tradeoff between the minimization of these impacts and the other objectives. The results should reduce the material and energy flows involved in construction and operation and enable decision makers to incorporate environmental costs and externalities into their actions and decisions. Life-cycle considerations and the growing importance of design-build-operate concepts will be key when addressing the challenge to design sustainable water supply systems to meet the needs of a growing global population, within the tolerance limits of the planet's natural resources.

This thesis presents the use of real options ‘in’ systems as applied to some case studies. However, there is still a long way to go, including the consideration of real options ‘on’ systems in water infrastructure management. Water utilities are usually asked to make large investments in highly uncertain financial markets. ROs ‘on’ systems can give valuable help by providing investments adaptable to uncertain future market conditions. This is a fundamental concern that has only been heightened by the latest financial crises. A number of objectives can be used in these models. The development of new climate-energy-economy models should take cost volatility into account, with the aim of testing different options and low carbon solutions at different scales and for key economic and societal sectors.

These future trends will certainly enrich this research work. This thesis contributes with a number of improvements to the design and operation of water distribution systems under uncertainty. The solving of real-world decision problems in the context of sustainable planning for infrastructure can be supported with these decision-aid tools.

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