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FCTUC FACULDADE DE CIÊNCIAS E TECNOLOGIA UNIVERSIDADE DE COIMBRA

OPTIMIZATION MODELS FOR WASTEWATER SYSTEMS PLANNING AT REGIONAL LEVEL: DETERMINISTIC AND ROBUST APPROACHES

Doctoral thesis

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Abstract

This thesis develops a set of optimization-based approaches addressing wastewater system planning at regional level. Regional wastewater systems are required for the collection and the treatment of the wastewater that is generated in a region before being discharged into a water body. These systems are of crucial importance to guarantee the quality of the water bodies, which is vital for the promotion of a sustainable development. Because of this, and also because wastewater systems solutions are costly and very difficult to reverse, it is important that they are planned efficiently. When such planning is made at regional level, it is possible to obtain better solutions with regard to costs, taking advantage of scale economies, while achieving a better environmental performance.

The proposed optimization models aim at finding the optimal layout for the sewer network, and for the location, type, and size of the pump stations and treatment plants to include in the system. The decisions on wastewater system planning involve two main issues: the setup and operation costs of infrastructure; and the water quality parameters to be met in the water body where the (treated) wastewater is discharged. The water quality varies along the river in accordance with the effluent discharges, and is assessed through environmental parameters such as dissolved oxygen, nitrogen, and phosphorus concentration.

The basic optimization model applied consists in a deterministic formulation with a cost-minimization objective. The objective function is subjected to different constraints to ensure that the sewer network will be designed according to hydraulic laws and regulations. In the single-objective deterministic approach, the water quality goals are included through constraints to ensure that the effluent discharges from each treatment plant will not create environmental damage. To enhance the prospect of simultaneous accomplishment of both environmental and cost objectives, a multi-objective deterministic approach is also proposed, making possible to identify solutions that are a good compromise with regard to conflicting objectives. The multi-objective model is

handled through the weighting method and consists of three objectives: minimization of capital costs; minimization of operating and maintenance costs; and maximization of dissolved oxygen.

Wastewater systems are subjected to several sources of uncertainty. Various scenarios can occur in the future depending on the behavior of a variety of variables such as demographic or environmental. Different robust approaches are developed in this thesis, aimed at finding solutions that will perform well under any likely scenario. The source of uncertainties considered are the flow of the river that receives the wastewater generated in a given region and the amount of wastewater generated, that depends on the future population.

This thesis is also concerned with model solving issues. The non-linear discrete optimization models are solved through an efficient simulated annealing algorithm enhanced with a local improvement procedure. The algorithm is termed efficient because its parameters were calibrated to ensure optimum or near-optimum solutions to the model within reasonable computing time. The calibration was performed using a particle swarm algorithm for a large set of test instances designed to replicate real-world problems.

Finally, the thesis presents *OptWastewater*, an easy-to-use computer program designed to be a decision support tool incorporating the different optimization models. In addition to being used for all the calculations involved in this thesis, it aims at making this type of approaches more likely to be used in practice.

Resumo

Nesta tese é apresentado um conjunto de abordagens de otimização para o planeamento regional de sistemas de drenagem e tratamento de águas residuais. Estes sistemas são necessários para coletar e tratar as águas residuais geradas numa região antes de serem descarregadas no meio hídrico recetor, sendo de importância crucial na manutenção da qualidade dos meios hídricos e vitais para a promoção de um desenvolvimento sustentável. Neste sentido, e uma vez que as soluções para os sistemas de águas residuais são dispendiosas e muito difíceis de alterar, é importante que sejam planeadas de forma eficiente. Ao efetuar tal planeamento a nível regional é possível não apenas obter as melhores soluções no que diz respeito aos custos, aproveitando vantagens de escala, mas também alcançar um melhor desempenho ambiental.

Os modelos de otimização propostos visam encontrar uma configuração ótima para a rede de coletores, e para localização, tipo e dimensões das estações elevatórias e estações de tratamento de águas residuais a incluir no sistema. As decisões de planeamento focam-se sobretudo em dois aspectos: os custos respeitantes à instalação, manutenção e operação dos equipamentos; e os indicadores de qualidade da água a serem cumpridos no meio hídrico que recebe os efluentes (tratados). A qualidade da água varia ao longo do meio hídrico recetor de acordo com as descargas de efluentes nele realizadas e é avaliada segundo indicadores ambientais como a concentração de oxigénio dissolvido, fósforo ou azoto.

O modelo base de otimização aplicado consiste numa formulação determinística com um objetivo de minimização de custo. A função objetivo está sujeita a diferentes restrições para assegurar que a rede de coletores é dimensionada de acordo com as leis e normas hidráulicas. Na abordagem determinística de um único objetivo, as metas de qualidade da água são incluídas através de restrições para assegurar que os efluentes descarregados a partir de cada estação de tratamento não provoquem impactos ambientais inaceitáveis. Para melhorar a expetativa de realização simultânea dos objetivos ambientais e de custos, uma abordagem multi-objetivo é desenvolvida,

tornando possível identificar as soluções que são um bom compromisso em relação a objetivos conflituantes. O modelo multi-objetivo é tratado através do método da ponderação e compreende três objetivos: minimização do investimento; minimização dos custos de operação e manutenção; maximização do oxigénio dissolvido.

Os sistemas de drenagem e tratamento de águas residuais estão sujeitos a várias fontes de incerteza. Vários cenários podem ocorrer no futuro dependendo do comportamento de diversas variáveis, nomeadamente demográficas ou ambientais. Diferentes abordagens robustas são desenvolvidas nesta tese, visando encontrar soluções que venham a ter um bom desempenho em qualquer cenário. A incerteza foi considerada ao nível do caudal do rio que recebe as águas residuais produzidas numa determinada região e das quantidades de efluentes gerados, que dependem da população no futuro.

Esta tese aborda também as técnicas de resolução dos modelos. Os modelos não-lineares inteiros mistos são resolvidos através de um algoritmo eficiente de recozimento simulado complementado por um algoritmo de pesquisa local. O algoritmo é denominado eficiente visto que os seus parâmetros foram calibrados para assegurar soluções ótimas ou quase ótimas para o modelo em um tempo de computação razoável. A calibração foi realizada empregando um algoritmo de enxame de partículas a um largo conjunto de instâncias de teste desenhadas para reproduzir problemas reais.

Por último, a tese apresenta *OptWastewater*, um programa de computador de uso fácil projetado para ser uma ferramenta de suporte à decisão incorporando os diferentes modelos de otimização. Além de ser usado para fazer todos os cálculos envolvidos na presente tese, *OptWastewater* visa tornar as abordagens desenvolvidas na tese mais susceptíveis de serem utilizadas na prática.

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OPTIMIZATION MODELS FOR WASTEWATER SYSTEMS PLANNING AT REGIONAL LEVEL: DETERMINISTIC AND ROBUST APPROACHES

Chapter 1

Introduction

1.1. Problem statement

Water has witnessed and sustained human evolution throughout history. But as the world's population grew and the standards of living rose, the pressure on water resources increased dramatically. In particular, water resources have suffered large impacts due to the escalating number of pollutants, resulting in environmental degradation and additional water stress problems. Today, in several countries, the demand for both supply and quality of water is no longer fulfilled. The subsequent water scarcity is among the main problems to be faced by the world in the XXIst century (UN 2006).

The importance of water is widely recognized, and the need to preserve its good quality has led to the definition of several environmental guidelines and regulations to restrict pollutant discharges into water bodies. In the European Union, the introduction of the *Water Framework Directive* (*Directive 2000/60/CE*) offered an integrated vision of water resources with the aim of achieving a "good water status" for all water bodies. For instance, rather than just imposing standards for the pollutant discharges, water quality standards are explicitly defined for the receiving water bodies through a river basin-scale approach. With the same goal of water sustainability, holistic approaches to water resources have been progressively applied in other developed countries, prompting similar water quality standards (e.g., *National Recommended Water Quality Criteria* in the United States, and *National Water Quality Management Strategy* in Australia).

The pollution problems faced by water bodies are extremely relevant in areas close to dense urban developments. Wastewater systems are required to collect and treat the generated wastewater before disposal, if good water quality is to be achieved. Although the implementation of wastewater systems may require large investments, these are likely to be largely recouped through the benefits obtained (WBCSD 2008). The infrastructure required for the drainage and treatment of wastewater consists primarily of sewer networks, pump stations, and wastewater treatment plants. In the past, wastewater systems were sized to combine sewage and rainwater, resulting in treatment issues and overflow-related problems. Thus, when building new systems, the trend is to employ separate sewage collection, even though similar problems may arise if no stormwater treatment is implemented (Burian et al. 1999, De Toffol et al. 2007). Because wastewater systems are costly, difficult to reverse, and essential to guarantee the quality of water bodies, they require complex planning processes. Such planning processes are often undertaken at local level for each city or part of a city. But a regional planning approach can provide better solutions with regard to costs, taking advantage of scale economies, while achieving a better environmental performance.

The research field of regional wastewater systems planning can be traced back to the 1960s. One of the first problems dealt with was the waste load allocation problem, i.e.

finding the optimal distribution of the level of pollutants to be removed at a number of wastewater point sources along a stream (Liebman and Lynn 1966, ReVelle et al. 1967). The other main problem addressed, which is at the core of this thesis, resides in finding an optimal solution for the configuration of the infrastructure to be installed in a regional wastewater system, considering emission standards and including wastewater transport (Deininger and Su 1973, Joeres et al. 1974). The search for regional wastewater system solutions should rely on optimization-based approaches to allow full exploration of possible planning alternatives. Several optimization models have been developed for this purpose, as presented in the surveys from Melo and Câmara (1994) and Whitlatch (1997) on the first optimization models applied. Along with the progress of the approaches proposed in the literature, evolving from simplified versions of the problem to more complex formulations, the techniques required to solve them were also improved. The works of Wang and Jamienson (2002) and Sousa et al. (2002) are examples of the application of modern heuristics to solve midsize regional wastewater system planning problems.

The models reported in the literature on regional wastewater system planning have typically involved single-objective formulations, mostly aimed at cost minimization. But there are other objectives in real-world decision-making problems, usually dealt with as constraints in the optimization models (e.g., economic, environmental, social and technical criteria). Growing awareness of multiple objectives in water resources problems encouraged the use of multi-objective formulations as described in Lee and Wen (1996), which used a multi-objective optimization model in a waste load allocation problem with various environmental and economic objectives. This type of problem was also addressed by Burn and Yulanti (2001) and Yandamuri et al. (2006), including equity as an additional objective. However, to the best of the author's knowledge, multi-objective approaches to regional wastewater system planning problems have not yet been developed.

Traditionally, regional wastewater system planning optimization models have been addressed through deterministic approaches, failing to explicitly consider the presence of uncertain variables and factors related, for example, with climate change or human population dynamics. To address water resources related problems, several stochastic approaches have been applied as discussed in Watkins and McKinney (1997), in which a robust optimization approach was also presented. Robust optimization approaches were introduced in a prominent paper by Mulvey at al. (1995), and consist in a scenario-based approach that incorporates risk aversion. In problems related to water systems planning, a promising literature has been recently devoted to robust optimization (e.g., Rosenberg and Lund 2009, Cunha and Sousa 2010). Although these approaches require a large computational effort, with the current computation capabilities its implementation is more and more justified (Kouvelis and Yu 1997).

Regardless of the benefits in using optimization-based approaches, there is still the need to bridge the gap between theory and practice (Fu et al. 2000). The same applies to regional wastewater system planning. Firstly, the studies developed on this subject are frequently founded on very small test instances, not comparable to real-world situations involving numerous decisions at many levels. Furthermore, engineers are often suspicious about models, and not receptive to the apparent complexity of the mathematical formulation and resolution of realistic models. Often, a user-friendly decision support tool is required for a decision-maker to apply the optimization model. But the existing software seldom matches the needs of decision-makers. Finally, there is frequently a mismatch between where the use of decision support tools can be most beneficial, at early planning stages, and where computer assistance is straightforward, at detail design stages.

1.2. Research goals

The purpose of this thesis is to develop optimization models for supporting regional wastewater system planning processes. These models should address regional wastewater system planning problems in such a way that reflects the needs and priorities for both decision-makers and practitioners, taking explicitly into account the water quality of the receiving water bodies. More specifically, the primary goals of the thesis are to provide:

1. Deterministic approaches to wastewater system planning at regional level. The main goal of the thesis is to develop realistic optimization models to search towards optimal solutions for the configuration of regional wastewater systems. To address the presence of conflicting objectives, a multi-objective model formulation should be attempted.

2. Robust approaches to wastewater system planning at regional level. To consider the presence of uncertainty and search towards optimal solutions in a variety of possible scenarios, robust optimization models are needed.

3. *An efficient solution method to solve the models.* In principle, the models require a large computing effort to be solved. Consequently, another key goal is to develop a

solution method that expeditiously provides good quality solutions for the models, and is efficient even for large and realistic problems.

4. *A decision support tool for implementing the models.* The last goal is to provide a decision support tool to implement the models and be used by third party users. To that end, a computer program with a user friendly interface should be developed.

1.3. Outline

This thesis is organized into nine chapters. All chapters, except the introduction (Chapter 1), research background (Chapter 2), and conclusion (Chapter 9), are based on scientific articles and stand as independent units. Consequently, they may be read separately, as they contain an introductory section, sections addressing problem modeling and solving, and a concluding section. Inevitably this format involves the repetition of a few background information and concepts throughout the thesis, but this is outweighed by the advantage to the reader of having an approachable document clearly defined into chapters that relate to specific subjects.

Despite the independence between chapters, this thesis is not a mere collection of articles. The chapters are interrelated and were planned to form a coherent document. Figure 1.1 is a diagrammatic representation of the thesis structure and makes explicit the relationships between chapters.

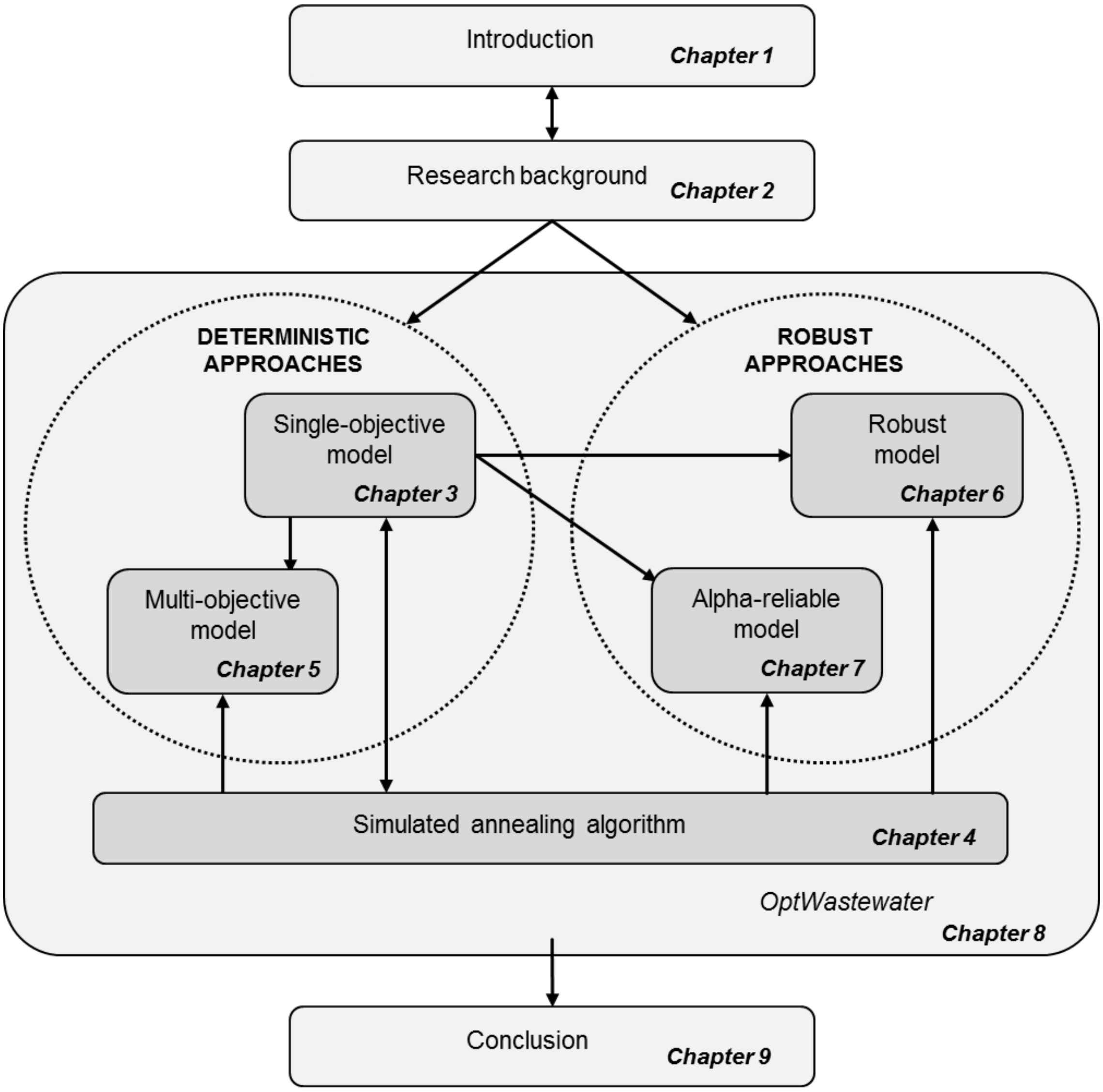


Figure 1.1 - Schematic figure of the research outline

The remainder of the thesis is organized as follows.

Chapter 2 continues the introduction by addressing the thesis background and significance, divided into two main categories: deterministic and robust approaches (Figure 1.1). In particular, Chapter 2 gives an overview of research topics that are innovative on wastewater system planning, providing some theoretical concepts that are not suitable to be discussed in the respective chapters due to the compressed style of scientific articles.

Chapter 3 describes in detail the basic model to deal with the regional wastewater system planning problem. It consists of a single-objective optimization model with a deterministic formulation. The model aims at helping to find a least-cost configuration for the (separate collection) wastewater system of a region, simultaneously meeting the water quality parameters defined for the river receiving the wastewater discharges, and complying with all other relevant regulatory aspects. The model's architecture is explained and prefaced with a review of the major contributions leading to its formulation. To make the approach able to deal with larger and more realistic problems, the heuristic method previously proposed to solve the model is upgraded to a hybrid algorithm (further detailed in Chapter 4) embracing a simulated annealing (SA) algorithm enhanced with a local improvement procedure. The potential usefulness of the model is illustrated by applying it to test instances. The model described in this chapter serves as foundation for the other models developed in the thesis.

Chapter 4 addresses the work done on the development of a heuristic method (SA algorithm enhanced with a local improvement procedure) to solve the models related to this thesis. The solution method is implemented for a version of the model presented in Chapter 3, aiming to ensure optimum or near-optimum solutions within reasonable computing time. Therefore, this chapter covers a vital component of this thesis. The main innovations in relation to previous work concern the parameters of the SA algorithm. Instead of the typical calibration of algorithm parameters through some trial-and-error procedure, the calibration is performed recurring to particle swarm optimization. The goal is to determine general expressions for the optimum value of the parameters of the SA algorithm as a function of the geographic and environmental characteristics of the problem to be solved. To this end, a set of test instances is generated according to partly random rules designed in order to replicate real-world problems. The solution method is evaluated from the standpoint of solution quality and computing effort.

Chapter 5 delineates a multi-objective optimization model that tries to identify solutions that are a good compromise with regard to conflicting objectives. The model focus on three objectives: minimization of capital costs; minimization of operating and maintenance costs; and maximization of the water quality in the receiving water body. The model is solved through the weighting method using the SA algorithm enhanced with a local improvement procedure presented in Chapter 4. Three test instances are used for illustrating the application of the model, and the results for different combinations of weights are discussed.

Chapter 6 proposes a robust approach to the regional wastewater system planning problem. This approach overcomes the drawback of the deterministic approaches by accommodating uncontrollable uncertainties, specifically in the flow of the river that receives the wastewater discharges. This is done through the consideration of different scenarios representing the possible states of the world. The model evolves from the one presented in Chapter 3 to three different robust optimization model formulations with the aim of finding solutions that are almost feasible and close to optimal in all the scenarios. The models are solved through the algorithm referred above. Their application is illustrated through a test instance representing a real-world situation, and the results of the three models are compared between them and compared with results obtained through the basic deterministic model.

Chapter 7 describes a robust approach as proposed in Chapter 6, but considering the uncertainty in the amount of wastewater generated by the population centers of a region. Based on scenario planning, an optimization model is developed to minimize the expected regret of the system with regard to costs, considering different levels of reliability. The various scenarios of wastewater amounts correspond to the different populations that might occur in the future, which are originated from a population projection that takes into account the demographic dynamics of the region. The potential usefulness of the model in real-world applications is illustrated through a case study involving a region located in Portugal.

Chapter 8 presents *OptWastewater*, an easy-to-use computer program developed in the course of this thesis. The program incorporates the optimization models described in the different chapters, and is designed to be a decision support tool aiming to make this type of approaches more likely to be used in practice. This chapter describes the data input that it requires, the solution methods it can apply, and the result outputs it provides. An example of application of *OptWastewater* is provided for three test instances.

Chapter 9, the concluding chapter, summarizes the research work described in the thesis and highlights its main contributions. The scope of future research is also covered.

1.4. Publications

As stated before, most research chapters of this thesis were written in the format of the international peer-reviewed journals where they are published or in review. With the exception of some layout-specific issues, they have not been altered in any meaningful way. Therefore, some notation may differ from chapter to chapter of the thesis. The citations for these chapters are as reported in Table 1.1.

Table 1.1 - Publications

Title	Journal	Status
Chapter 3		
Optimization model for integrated regional wastewater systems planning	*Journal of Water Resources Planning and Management*	Published (2009, Volume 135, Issue 1, pp 23-33)
Chapter 4		
An efficient simulated annealing algorithm for regional wastewater system planning	*Computer-Aided Civil and Infrastructure Engineering*	Published (2009, Volume 24, Issue 5, pp 359-370)
Chapter 5		
Multi-objective model for regional wastewater systems planning	*Civil Engineering and Environmental Systems*	Published (2010, Volume 27, Issue 2, pp 95-106)
Chapter 6		
Robust optimization approach to regional wastewater system planning	*Journal of Environmental Management*	In press (2012)
Chapter 7		
Regional wastewater system design under population dynamics uncertainty	*Journal of Water Resources Planning and Management*	Conditionally accepted

The research described in this thesis was also presented in several international conferences:

– The solution method described in Chapter 4 was improved with the discussion and the comments obtained during the *XII Simpósio Luso-Brasileiro de Engenharia Sanitária e Ambiental* (12th SILUBESA), Figueira da Foz, Portugal, March 13-17, 2006 (published in the conference proceedings), and during the *5th International Conference in Decision Making in Urban and Civil Engineering* (DMUCE 5), Montreal, Canada, June 14-16, 2006 (published in the conference proceedings, pages 2636-2646).

– The multi-objective model proposed in Chapter 5 was initially presented in *4th International Conference on Sustainable Water Resources Management*, Kos, Greece, May 21-23, 2007 (published in *Water resources management IV*, C.A. Brebbia and A.G. Kungolos, eds., WIT Transactions on Ecology and the Environment, Vol. 103, WIT Press, Southampton, U.K., pages 123-132).

– The robust approach of Chapter 6 was introduced in the *7th International Conference on Ecosystems and Sustainable Development* (ECOSUD 2009), Chianciano Terme, Tuscan, July 8-10, 2009 (published in *Ecosytems and Sustainable Development VII*, C.A. Brebbia and E. Tiezzi, eds., WIT Transactions on Ecology and the Environment, Vol. 122, WIT Press, Southampton, U.K., pages 591-599), and also presented during the *14th Encontro Nacional de Saneamento Básico / 14th Simpósio Luso-Brasileiro de*

Engenharia Sanitária e Ambiental (14th ENaSB / 14th SILUBESA), Porto, Portugal, October 26-29, 2010 (published in the conference proceedings).

- The article that underlies Chapter 8 was presented in the *4th Congresso Luso-Brasileiro para o Planeamento Urbano, Regional, Integrado, Sustentável* (PLURIS 2010), Faro, Portugal, October 6-8, 2010 (published in the conference proceedings), and was also presented during the *24th European Conference on Operational Research* (EURO 2010), Lisbon, Portugal, July 11-14, 2010.
- The basic optimization model with different objectives and constraints was applied to a case study based on a real world region and accepted to be presented during the *Strategic Asset Management of Water and Wastewater Infrastructure* (LESAM 2011), Mülheim an der Ruhr, Germany, September 27-30, 2011.

Chapter 2

Research background

This thesis addresses subjects that have not yet been covered in the literature of regional wastewater system planning. Although the significance of the planning problem of regional wastewater systems has been identified and addressed for more than half-century, little work has been done further than deterministic single-objective optimization models. The research presented here extends the problem of finding an optimal solution for the configuration of the infrastructure to be installed in a regional wastewater system to a modern approach involving more realistic and state-of-the-art optimization models and solution methods. The main contributions of this thesis on regional wastewater system planning fall into two primary categories: new deterministic approaches, and new robust approaches.

2.1. Deterministic approaches

The research described in this thesis was triggered by the optimization model for regional wastewater system planning described in Sousa et al. (2002), residing in the location and sizing components of both sewer networks and treatment plants involved in a regional wastewater system. To solve the nonlinear combinatorial optimization model of cost minimization, Sousa et al. (2002) implemented a modern heuristic consisting in a simulated annealing (SA) algorithm (Kirkpatrick et al. 1983, Cerny 1985). Its optimization approach lacked to explicitly take into account the water quality in the water bodies that receive the wastewater discharges. To overcome these aspects, Cunha et al (2004) made a first attempt to incorporate into the approach a water quality model in order to explicitly consider constraints on the quality of the receiving water body.

The optimization models described by Sousa et al. (2002) and Cunha et al (2004) were addressed in this thesis, with possible improvements identified and updated. In particular, it was recognized the need to make the approach able to deal with larger and more realistic problems, and thus the need to develop a more efficient solution method. As a result of this, the solution method was upgraded to a hybrid algorithm embracing an SA algorithm enhanced with a local improvement procedure, and its parameters were recalibrated. Therefore, in an initial step of the thesis the optimization approach was introduced in the format of a scientific journal article that was published and is presented in Chapter 3.

The optimization model and solution method presented in Chapter 3 sets the stage for the other chapters of this thesis. In particular, it helped identify that the solution method could be further improved with regard to some aspects. To mitigate the random nature of the SA algorithm a more sophisticated parameterization is required, that is, the calibration of the SA algorithm parameters to maximize the quality of the solution. These aspects are dealt with in Chapter 4 of the thesis, where an efficient SA algorithm is presented. The usual approach for the algorithm’s calibration consists in the manual modification of parameters, which is suitable if the algorithm contains only a small number of parameters with a limited step size in a given interval. For more complex situations this method is less feasible and there is the need to use automated procedures able to search continuously through the solution space. Therefore, Chapter 4 proposes an optimization approach to perform the SA algorithm calibration with the aim to maximize solution quality while minimizing computation time.

2.1.1. Simulated annealing calibration – Particle swarm

For the parameterization of the SA algorithm an optimization approach consisting in a Particle Swarm (PS) algorithm is developed. The PS algorithm is based on swarm intelligence techniques and was originally introduced by Kennedy and Eberhart (1995). The concept of swarm intelligence is inspired by the social behavior of groups of animals such as bird flocking, ant colonies, animal herding or fish schooling. The PS is a population based algorithm inspired by the emergent motion of, for instance, a flock of birds searching for food. The flock is called swarm, and the birds correspond to the individuals that are called particles and move towards the greatest amount of food corresponding to the optimal solution.

In the PS algorithm each particle i belonging to the swarm $\boldsymbol{I}$ is characterized by a position P corresponding to a solution value in terms of a given fitness (objective) function, with coordinates defined in $\boldsymbol{D}$-dimensional space. The particles of the swarm iteratively evolve in the space changing their position according to a velocity V as follows:

$$P_{id}^{k} = P_{id}^{k-1} + V_{id}^{k} \tag{2.1}$$

where P_{id}^{k} is the position of particle *i* at dimension *d* in iteration *k*; and V_{id}^{k} is the velocity of particle *i* at dimension *d* in iteration *k*.

The kinetics of the motion of the particles is affected by two fitness measures that are related to an individual and a social perspective. The individual perspective relates to the particle personal best position achieved in all the previous iterations, which is stored as P_{id}^{*}. The social perspective relates to the swarm cooperation, through the overall best position achieved by all particles in all the previous iterations (or by local neighborhood particles, in the neighborhood version of the algorithm) stored as P_{gd}^{*}.

The PS algorithm simulates the behavior of real swarms, combining the individual and social perspectives to define the trajectory of each particle in the solution space, which otherwise would keep the same velocity towards the infinity. Therefore, at each iteration the velocity V_{id}^{k} used to update the position of a particle is changed according to its previous velocity V_{id}^{k-1} and to both the individual and social perspectives. In a refinement of the PS formulation made by Shi and Eberhart (1998), an inertia weight was introduced to control the impact of the previous velocities on the current velocity, thereby influencing the importance ascribed to global and local search abilities. The resulting equation of velocity update can be expressed as:

$$V_{id}^{k} = w_i \times V_{id}^{k-1} + c_1 \times rand_1(\ ) \times \left(P_{id}^{*} - P_{id}^{k-1}\right) + c_2 \times rand_2(\ ) \times \left(P_{gd}^{*} - P_{id}^{k-1}\right) \tag{2.2}$$

where w_i is the inertia weight, c_1 and c_2 are positive constants, $rand_1(\ )$ and $rand_2(\ )$ are two random functions, P_{id}^{*} is the best position of particle *i* at dimension *d* in all previous iterations, and P_{gd}^{*} is the overall best position among all particles at dimension *d* in all previous iterations.

A large inertia weight facilitates a global search while a small inertia weight facilitates a local search. The velocity of each particle is limited by minimum and maximum limits. The strength of attractiveness either to the individual or global best position of the particles is defined by the positive constants. To mitigate the randomness of the PS algorithm, transforming it into a deterministic version, Trelea (2003) proposed some simplifications. Considering the random functions as uniform in the range [0,1], they can be sett to their expected value:

$$rand_1(\ ) = rand_2(\ ) = \frac{1}{2} \tag{2.3}$$

In addition, a new coefficient *b* is introduced as the average of the individual and social attraction constants c_1 and c_2. The inertia weight ascribing the importance to the previous velocity is represented through coefficient *a*. The resulting equation to iterate the velocities of the particles becomes:

$$V_{id}^{k} = a \times V_{id}^{k-1} + b \times \left(P_{id}^{*} - P_{id}^{k-1}\right) + b \times \left(P_{gd}^{*} - P_{id}^{k-1}\right) \tag{2.4}$$

where *a* and *b* are parameters.

Figure 2.1 shows graphically the mechanism of position update. The swarm (flock) of particles (birds) is “flying” in a field to find the location with the best solution (largest amount of food). This occurs in *D* dimensions. At each iteration *k* the PS algorithm define the new velocities of the particles using information about previous velocities, and the particle and social best positions achieved in all previous iterations. All particles will be attracted toward their own best and the global best position so far. In the subsequent iterations, the swarm, or at least some particles, are expected to find the global optimal positions and move towards the best solutions. Note that in each dimension the search space will be dealt independently, as the only link between the dimensions of the problem space is introduced via the objective function corresponding to the solution fitness.

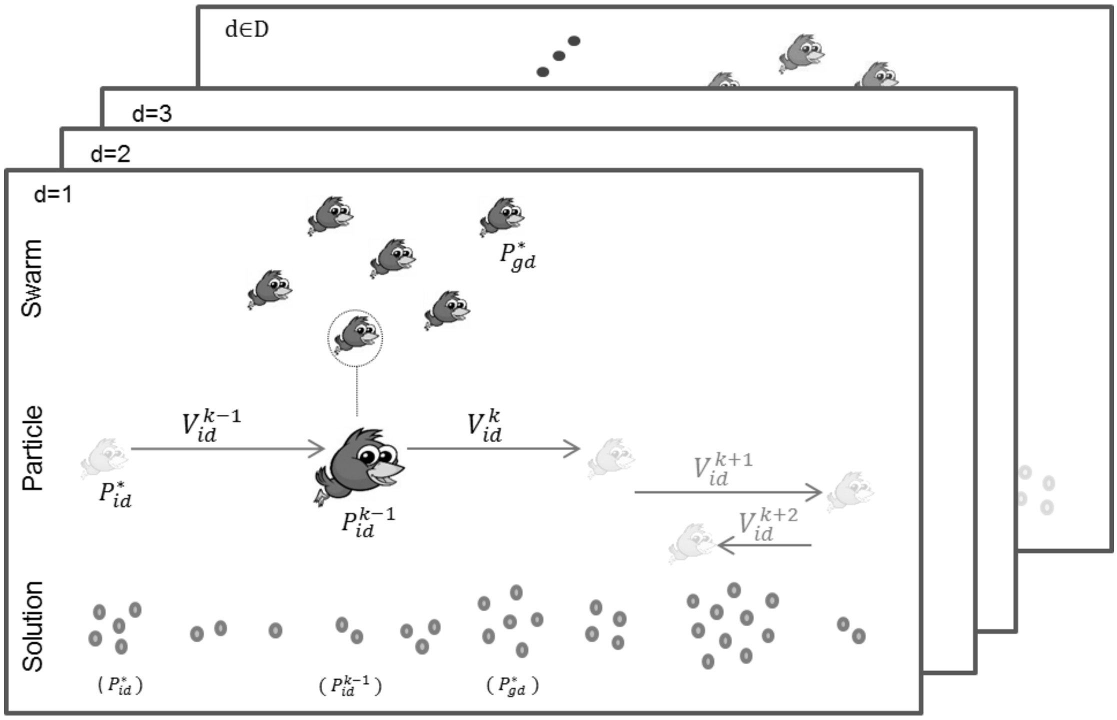


Figure 2.1 - Graphical illustration of the mechanism of position update

The basic steps of the PS algorithm are identified in Figure 2.2. It starts from a population initialization, with a random distribution of the particles along the space, and respective random initial velocities within a certain range of the space. Next, the new positions of the particles are defined according to equation (2.1). The individual best positions and the global best position are evaluated by comparing, in the current positions of the particles, their solution values in terms of a given objective with the values obtained in the positions taken on the previous iterations. Then, through equation (2.4) is possible to define the new velocity of the particles. The procedure ends when, after several iterations, the velocity becomes close to zero, that is, the change of the position taken by the particles would be insignificant.

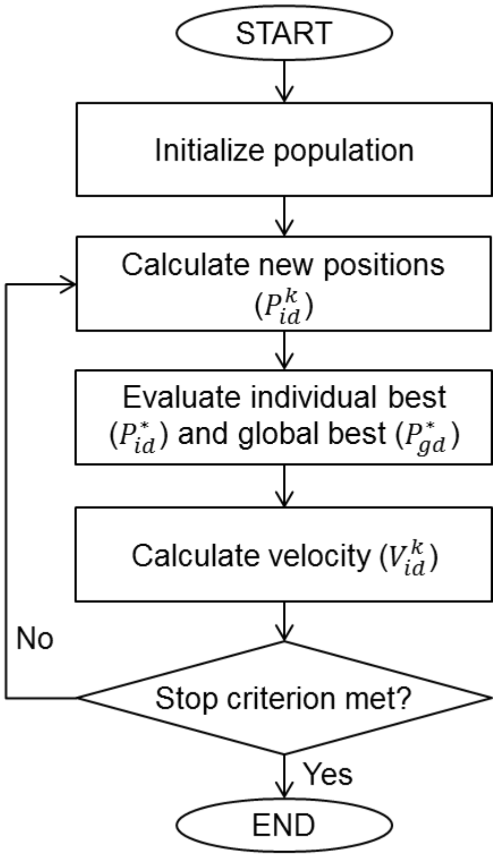


Figure 2.2 - Basic steps of a particle swarm algorithm

The search space of the PS algorithm is multidimensional, which fits the type of problem involved in the calibration of the different parameters of the SA algorithm, where there are different continuous variables that are expected to vary together. Other advantages of the PS algorithm are that it can be easily implemented and its computational requirements are low (Eberhart et al. 1996). The velocity, as well as the large number of particles contained in the swarm, guarantees a good coverage of all the search space, making the technique very well fitted to avoid local minima. In addition, the social cooperation allows a better fine-tune on the local search area, reducing the chance of missing the optimum.

The calibration approach presented in Chapter 4 aims to determine general expressions for the optimum value of the parameters of the SA algorithm as a function of the geographic and environmental characteristics of the problem to be solved. To that end, a large set of test instances is generated to replicate real-world problems. Then, the PS algorithm is used to determine optimum parameters of the SA algorithm for each test instance. Each parameter of the SA algorithm corresponds to a dimension in the PS algorithm space of solutions, with a fitness function given by system costs. Once the set of SA optimal parameters has been obtained, a multiple regression analysis with the respective geographic and environmental characteristics of the test instances is performed to establish general expressions for the optimum value of each parameter.

The approach developed in Chapter 4 allowed the optimization model to become more sophisticated and suited to deal with more realistic problems. Furthermore, in the pursuit for an approach more adequate to real-world problems, additional possible improvements were identified, such as the fact that alternative objectives could be considered.

2.1.2. Multi-objective optimization

Several objectives can be considered in planning problems, such as environmental, social or technical criteria. These can be taken into consideration as constraints in the single-objective (economic) optimization. In such way the regional wastewater system planning problems have typically been addressed through optimization models with a cost-minimization objective. However, an interesting alternative approach will allow decision-makers to enhance the prospect of simultaneous accomplishment of both environmental and cost objectives, and thereafter to make trade-off decision about selecting the best configuration of the system. This unique requirement of making trade-offs between these different objectives gives rise to formulating regional wastewater system planning as a multi-objective optimization problem.

A first issue in a multi-objective optimization problem is the identification of objectives, which may or may not be conflicting. Only those quantities that are competing should be treated as independent criteria whereas the others can be combined into a single criterion to represent the whole group. A small literature review including relevant criteria employed in recent works on water resources problems is presented in Chapter 5. In the same chapter, three objectives where selected to represent the essential economic and environmental concerns involved in wastewater systems planning: minimization of capital cost, minimization of operating and maintenance costs, and maximization of dissolved oxygen in the receiving water body. Then, based on the optimization model presented in Chapter 3, a multi-objective optimization model for regional wastewater system planning is described.

The concept of multi-objective efficiency was introduced by Pareto (1896), describing the Pareto frontier of efficient solutions, that is, the space of non-dominated solutions where no improvements can be achieved in any objective without deteriorating at least another objective. Methodologies for the approximation of the Pareto frontier have been proposed in the literature, but consisting in problems typically arduous, requiring excessive computing time for achieving a fine approximation of the Pareto frontier (Ruzika and Wiecek 2005). In addition, choosing a solution from the Pareto frontier can be, in itself, a difficult task. Indeed, although the solution to a multi-objective problem is a possible infinite set of Pareto points, we are only interested in specific locations of the frontier, to achieve promising solutions for the decision-maker who is not interested in the complexity and immensurable solutions of the Pareto frontier. To that end, the optimization model in Chapter 5 is handled through a weighting method to identify solutions that are a good compromise with regard to conflicting objectives. The weighting coefficients of the weighting method represent the relative importance desired for each criterion. They can be varied progressively as decision-makers acquire a deeper understanding of the problem they are faced with. Consequently, a small set of Pareto optimal solutions is generated and the tradeoffs are identified. The quality of the solutions can be evaluated through a sensitivity analysis. This approach results in a reduction of the search space and consequently a larger efficiency.

2.2. Robust approaches

Uncertainty can be considered as the lack of adequate information to make reliable decisions. Deterministic approaches assume that all model input variables are known with 100% certainty, which is rarely true for real-life systems. The need to model uncertainty has long been recognized as key to accurate planning, in particular in wastewater system planning where environmental concerns are present.

The aim to develop a trustworthy approach to regional wastewater system planning led to the need of incorporating uncertainty. Several parameters could be defined as uncertain, but for academic proposes it was decided to focus on two of the most pertinent parameters: the flow in the rivers where the treated wastewaters are discharged (discussed in Chapter 6), and the amount of population in the centers of the regions in study (discussed in Chapter 7). With respect to the flow in the rivers, it can be estimated using past observed data, giving rise to reference values that are assumed to represent the desired reliability. However, these do not explicitly contemplate the flow variability. The wastewater system, in particular the location of the treated wastewater discharges, should be designed taking into account the different possible outcomes for the river flow, so that even in small probability cases of low flows the water quality in the river remains proper. As regards to the amount of population, there is an inherent uncertainty derived from the projection of the future populations of the centers. Larger populations will lead to larger amounts of wastewater generated, and therefore the capacity requirements of the system infrastructure will be higher. The system should not be oversized but designed to remain reliable for low or high variants of population projection. In both cases of parameter's uncertainty, the decisions to be made continue to involve system costs and environmental impacts of the wastewater discharges.

Optimization models that take into account uncertain parameters are sometimes referred to as nondeterministic. Typically, models are formulated by selecting a forecast corresponding to, for instance, the most likely or mean-values for the uncertain parameters. To understand the impact of differences between data realizations and the assumed input parameters, sensitivity analysis is often employed. However, this is a reactive post-optimality procedure, which only examines the impact of data changes on the model. A proactive approach will explicitly incorporate some knowledge of the uncertainty in the decision-making stage to yield solutions less sensitive to data perturbations.

A common strategy to handle nondeterministic models is scenario planning, which requires the discretization of the uncertain parameter space, resulting in a set of possible states of the world called scenarios. Scenario planning approaches explicitly consider the different scenarios and aim to find solutions that are expected to perform well under all scenarios (Rockafellar and Wets 1991). A general model formulation containing scenario planning can be represented as follows:

$$
\begin{aligned}
&\text{Minimize} \quad f_s(x) \qquad s \in S \\
&\text{s.t.} \\
&g_i(x) \leq 0 \qquad i \in I \\
&h_{i,s}(x) \leq 0 \qquad i \in I \ , \ \ s \in S \\
&x_j \geq 0 \qquad j \in J
\end{aligned} \tag{2.5}
$$

where $f_s(x)$ is the objective function that depends on scenario *s*, $g_i(x)$ are the set of deterministic constraints, $h_{i,s}(x)$ are the set of uncertain constraints, and x_j refers to the set of decision variables.

For each scenario, $s \in S$, a probability p_s of its likelihood of occurrence can be assigned to reflect its relative importance in the uncertain environment, with $p_s > 0$ for all s and $\sum_{s \in S} p_s = 1$.

A possible proactive approach to deal with uncertainty through scenario planning is stochastic optimization. This formulation takes advantage of the fact that probability distribution governing the future scenarios is known or possible to estimate, and aim to find decisions that optimize the expected value of an objective function, defined by:

$$\sum_{s \in S} p_s \times f_s(x) \tag{2.6}$$

As mentioned before, Chapters 6 and 7 propose robust approaches to accommodate uncertainties in the flow of the rivers and amount of population in the centers, respectively. The first makes use of robust optimization models, and the latter is inspired by the alpha-reliable concept. Both approaches are introduced below.

2.2.1. Robust optimization

The idea of using scenario-based proactive models to deal with parameter uncertainty has received increasing attention, particularly following the termed robust optimization proposed by Mulvey et al (1995). Their robust optimization models consider an objective function that captures risk-averse behavior and recognizes infeasibilities that can inevitably arise. Indeed, their models are built on two distinct robustness concepts. A solution to an optimization is designated to be "solution robust" if it remains close to the optimal for all scenarios and "model robust" if it remains feasible for most scenarios. The general objective function of a robust optimization model is:

$$\text{Minimize} \;\; \sigma\left(f_s(x)\right) + \omega\rho(z_s) \qquad s \in S \tag{2.7}$$

where $\sigma\left(f_s(x)\right)$ is an aggregate objective function, $\rho(z_s)$ is a feasibility penalty function, z_s are measures of infeasibilities that depend on scenario s, and ω is a weight ascribing the acceptance level of infeasibilities.

The first term of (2.7) is an aggregate objective function corresponding to the solution robustness. Several possible formulations can be considered to this aggregate function. For instance, a possible choice consists in the worst-case analysis, as minimizing the maximum value of the objective function (such as cost), where maximum is taken over the set of all possible scenarios. In this case, an overdesigned system might be obtained. Another possible formulation is the mean value as used in stochastic formulations (2.6), which includes the probability of the different scenarios p_s. Other simpler formulations for the aggregate function are minimizing the expected regret, which is similar to minimizing the expected value but taken into account some degree of variability over the scenarios, or merely minimizing the objective function, suitable when its values are not conditioned on the scenario realizations (e.g. design variables such as installation costs). Two choices of aggregate functions were focused on Mulvey et al. (1995) aimed at high risk decisions: the expected utility, and the mean/variance. The former addresses risk aversion, but requiring an additional information burden for the risk tolerance level decision. The latter also addresses risk aversion, using variance as a measure of variability. This mean/variance formulation balances the tradeoffs between expectation and variance of the objective function through a weight λ, as follows:

$$\sum_{s \in S} p_s \times f_s(x) + \lambda \sum_{s \in S} p_s \times \left(f_s(x) - \sum_{s \in S} p_s \times f_s(x) \right)^2 \tag{2.8}$$

The second term of (2.7) is a feasibility penalty function corresponding to the model robustness. The inclusion of a penalty function is particularly meant to handle cases where no feasible solution is possible for every scenario. This penalty function will consider the violation of some constraints by the least amount. It can also be applied to define a degree of feasibility for the model. Mulvey et al. (1995) suggested two types of penalties. The exact penalty function is applicable to problems where either positive or negative violations are of interest. An example of an exact penalty for positive violations is:

$$\sum_{s \in S} p_s \times \max\{0, z_s\} \tag{2.9}$$

The quadratic penalty, for the case when both positive and negative violations should be avoided, can be given by:

$$\sum_{s \in S} p_s \times z_s^{\ 2} \tag{2.10}$$

Assuming a robust optimization model essentially combining an aggregate function consisting in the mean/variance formulation (2.8) with a feasibility quadratic penalty function for positive and negative violations (2.10), the formulation of such objective function of the model can be written as:

$$\text{Min} \ \sum_{s \in S} p_s \times f_s(x) + \lambda \sum_{s \in S} p_s \times \left(f_s(x) - \sum_{s \in S} p_s \times f_s(x) \right)^2 + \omega \sum_{s \in S} p_s \times z_s^{\ 2} \tag{2.11}$$

where λ and ω are weights.

The objective function (2.11) has three terms. The first term corresponds to the expected value of the variable that is affected by uncertainty and is to be minimized, such as cost. The second term represents the variance of the same variable. The third term penalizes the infeasibilities through a quadratic function. The weights λ and ω ascribe the importance of each term, and can be varied to analyze the tradeoffs between mean, variance and the penalty function, making it a multi-objective approach. Indeed, the first two terms of the objective function measure the solution robustness, which has also a tradeoff to the model robustness contained in the third term.

Several robust optimization models can be developed for diverse applications of real-world problems, as discussed by Mulvey et al. (1995). Based on the concept of robust optimization, in Chapter 6 of this thesis are proposed three robust optimization models corresponding to three different ways of capturing uncertainty in the flow of the river that receives the wastewater discharges. The general purpose of the models is to find a wastewater system configuration that, regardless of which scenario occurs, is feasible and close to optimal when cost and water quality objectives are considered. The models evolve from the one presented in Chapter 3, and are inspired by other robust optimization models presented for different problems. The first robust optimization model is inspired by the model developed in Laguna (1998) for the telecommunications systems capacity expansion, and consists of an aggregate function based on cost minimization with a penalty function involving the water quality of the river receiving the wastewater discharges. This penalty is exact, only for positive violations, but also a quadratic function to strength significance of larger deviations from the ideal. The second model was primarily developed for the portfolio immunization problem (Dembo 1991) and consists of a quadratic aggregate function to enforce solution robustness through regret for optimal costs in each scenario, and a penalty function similar to the first model. The third model has an objective function similar to (2.11), which is based on the robust formulation developed by Malcolm and Zenios (1994) for the power systems capacity expansion problem. This last model consists of an aggregate objective of a mean/variance formulation for the water quality in the river, combined with a penalty function in terms of the regret for the costs.

2.2.2. Alpha-reliable expected regret

A different robust approach based on scenario planning and on the same principle as robust optimization of capturing risk aversion was developed by Daskin et al. (1997). The authors introduced the notion of alpha-reliable minimax regret to optimize the worst-case performance over a set of scenarios. The minimax approaches make use of scenario planning to deal with problems with uncertain parameters through robustness measures such as minimax cost and minimax regret. A minimax cost/regret solution is a solution for which the maximum cost/regret over all scenarios is minimized. The regret is the deviation between the value of a solution adopted in an uncertain context and the value of the solution that would have been adopted if there was no uncertainty (Loomes and Sugden 1982). If V_s is the value of the solution under scenario s

$$V_s = f_s(x) \qquad s \in S \tag{2.12}$$

then the regret associated with scenario s is given by:

$$R_s = V_s - \hat{V}_s \qquad s \in S \tag{2.13}$$

where R_s is the value of the regret, and $\hat{V}_s$ is a constant representing the value of the best solution that could be adopted under scenario s.

The maximum regret considering the set of possible scenarios is:

$$\max\{R_s\} \qquad s \in S \tag{2.14}$$

The minimization of the maximum regret does not require the knowledge of scenario probabilities and is risk averse in the sense that it avoids that the solution will be particularly bad in some worst-case scenarios. However, since the minimax regret might focus on a few worst-case scenarios that are unlikely to occur, the alpha-reliable minimax regret attempts to overcome this drawback by taking into account the probabilities of the scenarios, and endogenously excluding in the solution some of these low probability scenarios. The formulation of such alpha-reliable model can be written as follows:

$$
\begin{aligned}
&\text{Min } W \\
&\text{s.t.} \qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad\qquad (2.15) \\
&R_s - \left(V_s - \hat{V}_s\right) = 0 \quad s \in S \\
&\sum_{s \in S} p_s \times Z_s \geq \alpha \\
&W - R_s + m_s\left(1 - Z_s\right) \geq 0 \quad s \in S \\
&g_i(x) \leq 0 \quad i \in I \\
&h_{i,s}(x) \times Z_s \leq 0 \quad i \in I \ , \ s \in S \\
&x_j \geq 0 \quad j \in J
\end{aligned}
$$

where W is the α-reliable minimax regret of the solution to be implemented, Z_s is a binary variable that takes the value 1 when the scenario belong to the reliability set and 0 otherwise; m_s is a large constant specific to scenario s, and α is the value for the reliability.

The alpha-reliable minimax regret is intended to make some decision models more realistic and less conservative, capturing the risk aversion by restricting the scenario space through a specified reliability level α. The minimax regret solution is computed only over an endogenously selected subset of scenarios, the reliability set, whose collective probability of occurrence is at least α. The maximum regret is defined through W, taking into account the regret of individual scenarios and the decisions regarding which scenarios to include in the reliability set. To this end, m_s is constant that must be set large enough so that $R_s - m_s \leq 0$ for scenarios not included in the reliability set. The traditional minimax regret problem is a particular case in which α = 1.0.

A similar approach to the alpha-reliable concept is dealt with in Chapter 7 of this thesis. Instead of using the maximum regret, it was decided to use the expected regret, equivalent to expected opportunity loss, given by:

$$\sum_{s \in S} p_s \times R_s \tag{2.16}$$

The expected regret is the regret for each possible state of the world multiplied by the probability of that state's occurrence. In a minimization of the expected regret, the model takes into account the set of scenarios and their probabilities in a similar way to the optimization of the expected value of the solution in stochastic formulations. Nevertheless, the use of the expected regret additionally takes into account possible solutions with large losses for some scenarios.

Through the use of the alpha-reliable concept together with the minimization of the expected regret, the scenario space can be restricted to enable the consideration of some infeasibilities as occurs in robust optimization. Unlike to the minimax regret, the expected regret seeks a system design less concerned with the most extreme and erratic conditions, as that is closer to what happens in real planning situations. In addition, the most relevant scenarios are given larger importance as their probabilities are explicitly taken into consideration in the expected regret formulation, which does not happen in minimax approaches.

The alpha-reliable expected regret formulation can be written as follows:

$$
\begin{aligned}
&\text{Min } W \\
&\text{s.t.} \qquad\qquad (2.17)\\
&R_s - \left(V_s - \hat{V}_s\right) = 0 \quad s \in S \\
&\sum_{s \in S} p_s \times Z_s \geq \alpha \\
&W - \sum_{s \in S} p_s \times R_s \times Z_s = 0 \\
&g_i(x) \leq 0 \quad i \in I \\
&h_{i,s}(x) \times Z_s \leq 0 \quad i \in I \;,\; s \in S \\
&x_j \geq 0 \quad j \in J
\end{aligned}
$$

where W is the α-reliable expected regret of the solution to be implemented.

The alpha-reliable expected regret captures risk aversion by restricting the scenario space through a specified reliability level α. The solution is computed only over an endogenously selected reliability set of scenarios, whose collective probability of occurrence is at least α. The expected regret is defined through *W*, taking into account the probability of each scenario, their respective regret and the decisions regarding which scenarios to include in the reliability set.

In Chapter 7, the model presented in Chapter 3 is extended to a formulation based on the model with the objective of minimizing the alpha-reliable expected regret of the system (2.17). The regret associated with a scenario is given by the difference between the costs of the solution implemented and the best costs that could be obtained under that scenario. This alpha-reliable model will lead to robust solutions, which are near-optimal and feasible with a certain level of reliability. Indeed, it allows that some facilities are not designed to some worse-case scenarios depending on the chosen reliability. In a variation of the model formulation, some facilities are allowed to be operating under undesirable conditions, but with the solution still feasible for all scenarios. Chapter 7 also presents a comparison with results obtained with a model consisting in an expected regret minimization without including reliability measures. As mentioned previously, the alpha-reliable expected regret model and respective variations are applied for a case study with a source of uncertainty in the population of the centers where the wastewater is generated. This uncertainty stems from the future population projection for the region being studied, which is converted to a set of possible scenarios as also described in Chapter 7 of this thesis.

Chapter 3

Optimization model for integrated regional wastewater systems planning

3.1. Introduction

Water is a major natural resource under threat in many parts of the World. The human activities developed close to water bodies may have a great impact upon their physical, chemical, and biological conditions, and can considerably affect the ecological state of animal and vegetal riverine communities. One of the main sources of water pollution is the wastewater generated in urban areas.

The pollution problems faced by river waters are extremely relevant in the European Union (EU) because of the large population density and high urbanization degree that characterizes most of their territory, and also because of the big, sometimes antiquated industrial complexes located in their cities.

The recognition of this situation led the EU to the adoption of the *Urban Wastewater Treatment Directive* in 1991 (*Directive 91/271/EEC*, modified by *Directive 98/15/EC*). According to this directive, all urban areas of all Member States should have been provided with collecting systems for urban wastewater, at the latest by December 31, 2000 for those with a population equivalent (p.e.) of more than 15,000, and at the latest by December 31, 2005 for those with a p.e. between 2,000 and 15,000. In spite of the efforts made since the directive was adopted, until very recently the wastewater generated in 183 of the 556 EU cities with populations over 150,000 was discharged either completely untreated or inadequately treated into rivers and other water bodies (EC 2004).

The essential elements of the *Urban Wastewater Treatment Directive* were recently incorporated into a broader directive, the *Water Framework Directive* (WFD) (*Directive 2000/60/CE*). In this directive, where the EU establishes the main guidelines for the water resources policy of Member States, "good water status" is the goal to be fulfilled in 2015 and Integrated Water Resources Management (IWRM) is the approach to be followed for achieving the goal.

The implementation of the WFD (through the IWRM approach) requires knowledge and skills that still need to be developed. In particular, it requires a better understanding of the cause–effect relationships that characterize the response of water resources systems to anthropogenic actions. Further, as explicitly recognized in EC (2003), it requires the development of decision-support tools where these cause–effect relationships are taken into account. When the number of possible courses of action is very large, which often occurs with regional wastewater systems problems, efficiency of decision-support tools can be improved through use of optimization models.

In this chapter, we present an optimization model for regional wastewater systems planning. The model is aimed at helping to determine the best possible configuration for the wastewater system of a region taking economic, environmental, and technical criteria explicitly into account. The model can be used separately or as a building block of a large decision-support tool designed to cover all (or most of) the issues involved in the implementation of an IRWM approach (in the EU or elsewhere).

The plan for the chapter is as follows. First, we present the problem addressed by the optimization model and review the literature dedicated to it over the last 40 years. Next, we show how we formulated the model and designed the method for solving it. Then, we illustrate the usefulness of the model through its application to three test problems. In the final section, we summarize the main contents of this chapter.

3.2. Problem presentation

The setting for the application of the optimization model dealt with in this chapter is a region with several population centers. The wastewater generated at these centers must be drained into a river (or a set of rivers).

The problem to be solved consists in determining the least-cost solution for the wastewater system of the region, simultaneously meeting the water quality parameters defined for the river and complying with all other relevant regulatory aspects (e.g., minimum diameter of sewers, maximum velocity of flow in sewers, etc.). The parameters generally taken into account when evaluating water quality include dissolved oxygen, biochemical oxygen demand, nitrogen, and phosphorus. Dissolved oxygen is considered to be one of the most crucial environmental parameters. The species that can live in rivers strongly depend on the level of this parameter. In particular, fish are very vulnerable to the depletion of oxygen provoked by the introduction of organic matter from untreated sewage. During the conversion of the organic matter into inorganic matter oxygen is consumed and then compensated by reaeration. However, it is important to evaluate the critical level attained by the oxygen during this depletion–reaeration process. Nitrogen, in its various forms, can cause diverse problems in natural waters. So, the consideration of all forms of nitrogen is crucial to guarantee good prediction capabilities of the system's behavior. The nitrogen cycle in natural aerobic waters is a stepwise transformation from organic nitrogen to ammonia, to nitrite, to nitrate, and finally to nitrogen gas that is released into the atmosphere. Kjeldahl nitrogen (organic nitrogen plus ammonia) allows the evaluation of the future production of nitrites and nitrates. In fact, the hydrolysis of organic nitrogen creates ammonia that is converted into nitrite and nitrate through a procedure called nitrification. High concentration of unionized ammonia is toxic for fish and high concentrations of nitrate are dangerous for producing drinking water. Nitrogen and phosphorus are nutrients that can impact plant biomass, therefore being important factors for controlling eutrophication.

A solution to the problem comprises the following ingredients: layout of the sewer network that will connect the population centers with the river; diameter of the sewers; location, type, and capacity of the treatment plants where the wastewater will be processed before being discharged into the river; location and capacity of the pump stations that will have to be installed to elevate wastewater if it is unfeasible or uneconomic to drain it by gravity.

The most important costs to be taken into account when evaluating a wastewater system are: installation and maintenance of sewers; and installation, operation (including energy), and maintenance of treatment plants and pump stations. These costs are incurred in different periods of time and must be discounted to the initial period (or annualized).

Many solutions for this type of problem can be envisaged. They range from solutions where each population center of a region treats wastewater in its own treatment plant to solutions where all the wastewater produced in the region is sent to a single treatment plant. The concentration of treatment plants may be quite effective in terms of treatment plant costs, because of the economies of scale it allows to make, but may be rather ineffective with regard to sewer network costs, whereas the opposite occurs with the dispersion of treatment plants. In addition, the concentration of treatment plants is likely to make the verification of water quality standards difficult, because large quantities of wastewater will be rejected in a small number of river sections. In principle, the more effective solutions in terms of total cost and environmental impact will lie somewhere between total concentration and total dispersion of treatment plants.

3.3. Literature review

Optimization models are being applied to regional wastewater systems planning since the early 1960s. The first attempts to formulate and solve these types of models were made by Lynn et al. (1962), Deininger (1965), and Loucks et al. (1967), who used linear programming. After that, up until the 1990s, a wide variety of approaches were applied: Graves et al. (1972) and Smeers and Tyteca (1982) used nonlinear programming (the latter, in combination with a shortest-path algorithm); Converse (1972) and Klemetson and Grenney (1985) used dynamic programming; Wanielista and Bauer (1972), Joeres et al. (1974), and Brill and Nakamura (1978) used linear mixed-integer programming; and McConagha and Converse (1973), Weeter and Belardi (1976), Lauria (1979), Melo (1992), and Voutchkov and Boulos (1993) used different types of classic heuristic methods. For a detailed survey of the models presented in the literature during this period, see Melo and Câmara (1994). With regard to these and other early models, it is necessary to point out here that they did not address, at least explicitly, some of the salient features of wastewater systems planning problems. Indeed, several simplifications were introduced in the models to allow the utilization of the available optimization techniques (e.g., the allocation of wastewater to treatment plants was determined without taking into account the whole design of the sewer networks; the location of treatment plants along rivers was calculated without taking into account the impact of wastewater discharges on water quality; the impact of wastewater discharges was assessed without using an advanced water quality model, etc.).

The problems involved in regional wastewater systems planning can only be dealt with properly if the corresponding optimization models include nonlinear cost functions for the installation, operation, and maintenance of sewer networks, treatment plants, and pump stations, take into account the nonlinear hydraulic behavior of sewer networks, comprise advection–diffusion differential equations to represent water quality dynamics, allow for yes or no decisions regarding the location of treatment plants and pump stations, consider the diameters commercially available for sewers, etc. This means that the models to be used must be mixed integer and nonlinear. These types of models can only be solved to (guaranteed) exact optimality under assumptions that regional wastewater systems planning problems typically do not satisfy. The alternative is to resort to heuristic methods. Until the 1980s, the heuristic methods available would frequently lead to local optimum solutions distant from global optimum solutions because of the gradient-based search strategy they applied. During the 1980s, a new kind of heuristic methods was devised. These modern heuristics, which are often inspired in natural processes, apply search strategies that can avoid local optimum solutions, and have become very popular among scientists and engineers [surveys on modern heuristics are available, for instance, in Aarts and Lenstra (2003), and Michalewicz and Fogel (2004)]. Many applications of modern heuristics to water resources and hydraulic systems planning and management problems have been reported in the literature [e.g., among the most influential, Dougherty and Marryott (1991), McKinney and Lin (1994), and Savic and Walters (1997)]. However, applications to wastewater systems are relatively rare. Most of them focus on real-time wastewater systems control (e.g., Schutze et al. 1999; Rauch and Harremoes 1999) and waste load allocation (e.g., Burn and Yulianti 2001; Cho et al. 2004), and employ genetic algorithms. To our knowledge, the only articles reported on scientific journals on the application of modern heuristics to regional wastewater systems planning problems (with the components referred to in the previous section) are due to Sousa et al. (2002) and Wang and Jamieson (2002). The model presented in Wang and Jamieson (2002) is aimed at determining a minimum-cost solution for the location of treatment plants along a river, as well as the optimum degree of treatment to perform at the treatment plants, and is solved through a genetic algorithm. This model does not consider sewer network design issues. The river water quality dynamics is only analyzed in terms of biochemical oxygen demand and is modeled by means of artificial neural networks. The model described in Sousa et al. (2002) takes into account, simultaneously, sewer network design and treatment plant (and pump station) location issues, and is solved through a simulated annealing algorithm incorporated in a geographic information system-based (GIS-based) computer program. Within this model, river water quality issues are only dealt with implicitly, through the inclusion of limits on the maximum amount of wastewater to be processed at the treatment plants.

3.4. Model formulation

The objective function, the various sets of constraints, and the size of the optimization model developed to represent the regional wastewater systems planning problem introduced earlier are presented here in separate subsections. The notation is presented in Table 3.1.

3.4.1. Objective Function

The planning objective is to minimize the total costs involved in the installation, operation, and maintenance of the sewer network and the wastewater treatment plants. This objective can be formulated within an optimization model as follows:

$$\mathrm{Min} \sum_{(i,j)\in\mathbf{S}} C_{(i,j)}\left[Q_{(i,j)}, E_{(i,j)}, x_{(i,j)}, y_{(i,j)}\right] + \sum_{k\in\mathbf{N}_T} \sum_{p\in\mathbf{T}} C_{kp}\left(QT_k, z_{kp}\right) \tag{3.1}$$

where $C_{(i,j)}$ is the discounted costs for installing, operating, and maintaining a sewer connecting node i to node j and a possible pump station to elevate wastewater from node i to node j; and C_{kp} is the discounted costs for installing, operating, and maintaining a treatment plant of type p at node k.

The first term of this objective function corresponds to sewer network and pump station costs, which will depend on the wastewater flow carried by the sewers and on the difference between the hydraulic heads at the extremities of sewers. The second term corresponds to treatment plant costs, which, for a given type of treatment plant, depend on the amount of wastewater treated there. Existing equipments can be easily dealt with through this objective function—it suffices to handle them as new equipments with zero installation costs (and maximum capacity equal to their capacity).

The evaluation of wastewater flows and hydraulic heads is made through a hydraulic model. Within this model, the wastewater flow carried by each sewer depends, through the Manning–Strickler formula, on the slope and on the diameter of the sewer, given the length of the sewer and the type of material it is made of. If the difference between the hydraulic heads at the extremities of a sewer does not allow gravity flow, a pump station with the power required to elevate flow is introduced in the network.

With regard to the objective function, it is necessary to emphasize here that the adoption of a cost-minimization objective does not signify less concern with environmental issues, because, in an optimization model, the most important objectives are often expressed through constraints. Indeed, what the objective function signifies is that we will be looking for the least-cost solution consistent with the objectives specified for water quality through the constraints, which can be extremely exigent.

Table 3.1 - Notation

Sets	
S	set of possible sewers
N	set of nodes (population centers plus possible intermediate nodes plus possible treatment plants)
$\mathbf{N}_{\boldsymbol{P}}$	set of population centers
$\mathbf{N}_{\boldsymbol{I}}$	set of possible intermediate nodes (these nodes may be needed to allow an appropriate representation of topography and/or the early regrouping of sewers)
$\mathbf{N}_{\boldsymbol{T}}$	set of possible treatment plants
T	set of treatment plant types
R	set of river sections
Decision Variables	
$Q_{(i,j)}$	flow carried from node *i* to node *j*
$E_{(i,j)}$	difference of hydraulic heads between node *i* to node *j*
QT_k	amount of wastewater conveyed to a treatment plant located at node *k*
$x_{(i,j)}$	binary variable that is equal to one if there exists a sewer to carry wastewater from node *i* to node *j*
$y_{(i,j)}$	binary variable that is equal to one if there exists a pump station for elevating wastewater from node *i* to node *j*
z_{kp}	binary variable that is equal to one if there exists a treatment plant of type *p* at node *k*
DO_r, N_r, P_r, and Nkj_r	total dissolved oxygen, total nitrogen, total phosphorus, and Kjeldahl nitrogen in river section *r*
Parameters	
QP_i	amount of wastewater produced at node *i*
$Q_{\mathrm{min}_{(i,j)}}$	minimum flow allowed in the sewer connecting node *i* to node *j*
$Q_{\mathrm{max}_{(i,j)}}$	maximum flow allowed in the sewer connecting node *i* to node *j*
$QT_{\mathrm{max}_{kp}}$	maximum amount of wastewater that may be treated at node *k* with a treatment plant of type *p*
$\mathrm{DO_{min}}$, $\mathrm{N_{max}}$, $\mathrm{P_{max}}$, and $\mathrm{Nkj_{max}}$	minimum or maximum total dissolved oxygen, total nitrogen, total phosphorus, and Kjeldahl nitrogen in a river section

3.4.2. Continuity Constraints

The continuity constraints state that all nodes, as well as the system in general, must be in equilibrium with regard to wastewater inflows and outflows. They can be formulated as follows:

$$\sum_{j \in \mathbf{N} | (i,j) \in \mathbf{S}} \left(Q_{(j,i)} - Q_{(i,j)} \right) = -QP_i , \ \forall i \in \mathbf{N}_P \tag{3.2}$$

$$\sum_{j \in \mathbf{N} | (i,j) \in \mathbf{S}} \left(Q_{(j,i)} - Q_{(i,j)} \right) = 0, \ \ \forall i \in \mathbf{N}_I \tag{3.3}$$

$$\sum_{j \in \mathbf{N} | (j,k) \in \mathbf{S}} Q_{(j,k)} = QT_k , \ \ \forall k \in \mathbf{N}_T \tag{3.4}$$

$$\sum_{i \in \mathbf{N}_P} QP_i = \sum_{k \in \mathbf{N}_T} QT_k \tag{3.5}$$

Constraints (3.2) apply to population center nodes, where there is an inflow of wastewater into the sewer network, constraints (3.3) apply to intermediate nodes, and constraints (3.4) apply to treatment plant nodes, where there is an outflow of wastewater from the sewer network. Constraint (3.5) ensures that all the wastewater produced in the region will be sent to a treatment plant.

3.4.3. Capacity Constraints

The capacity constraints specify the limits to the size of sewers and treatment plants that must be verified. They can be formulated as follows:

$$QT_k \leq \sum_{p \in \mathbf{T}} QT\mathrm{max}_{kp} \, z_{kp} , \ \ \forall k \in \mathbf{N}_T \tag{3.6}$$

$$\sum_{p \in \mathbf{T}} z_{kp} \leq 1, \ \forall k \in \mathbf{N}_T \tag{3.7}$$

$$Q\text{min}_{(i,j)}.x_{(i,j)} \leq Q_{(i,j)} \leq Q\text{max}_{(i,j)}.x_{(i,j)}, \ \forall (i,j) \in \mathbf{S} \tag{3.8}$$

Constraints (3.6) and (3.7), together, ensure that the flow processed at the treatment plants does not exceed their capacity (which depends on the type of plant). Constraints (3.8) guarantee that the wastewater flow in all sewers will be comprised between some minimum and maximum values. These values can be defined through the Manning–Strickler formula taking into account the appropriate (or legal) values for the diameter and the slope of the sewers, and for the velocity of flow in sewers.

3.4.4. Environmental Constraints

The environmental constraints specify limit values for the parameters used to characterize river water quality. They can be formulated as follows:

$$\mathrm{DO}_r\left(QT_1,\ldots,QT_r\right) \geq \mathrm{DO}_{\min}, \ \forall r \in \mathbf{R} \tag{3.9}$$

$$\mathrm{N}_r\left(QT_1,\ldots,QT_r\right) \leq \mathrm{N}_{\max}, \ \forall r \in \mathbf{R} \tag{3.10}$$

$$\mathrm{P}_r\left(QT_1,\ldots,QT_r\right) \leq \mathrm{P}_{\max}, \ \forall r \in \mathbf{R} \tag{3.11}$$

$$\mathrm{Nkj}_r\left(QT_1,\ldots,QT_r\right) \leq \mathrm{Nkj}_{\max}, \ \forall r \in \mathbf{R} \tag{3.12}$$

Constraints (3.9) are included to guarantee appropriate dissolved oxygen concentrations. These concentrations depend, for each river section, on the wastewater discharged in the section and all upstream sections, and on the characteristics of the river (cross-sectional area, flow, etc.).

The evaluation of dissolved oxygen concentrations is made through a water quality model where the following aspects are considered: atmospheric reaeration, photosynthesis, respiration, sediment oxygen demand, carbonaceous organic matter oxidation, and nitrification. This means that, in the advection-diffusion equation

$$\frac{\partial C}{\partial t} = \underbrace{\frac{1}{A}\frac{\partial}{\partial x}\left(AE\frac{\partial C}{\partial x}\right)}_{\text{Dispersion}} - \underbrace{\frac{1}{A}\frac{\partial}{\partial x}(AUC)}_{\text{Advection}} + \underbrace{\frac{dC}{dt}}_{\text{Kinetics}} + \underbrace{S}_{\substack{\text{Sources}\\ \text{or sinks}}} \tag{3.13}$$

the kinetics for the dissolved oxygen is given by (Chapra 1997)

$$\begin{aligned}\frac{d\mathrm{DO}}{dt} = {} & \underbrace{K_2(\mathrm{DO}_{\mathrm{sat}} - \mathrm{DO})}_{\text{Atmospheric Reaeration}} + \underbrace{(\alpha_3\mu - \alpha_4\rho)\mathrm{BM}}_{\text{Photosyntesis and respiration}} \\ & - \underbrace{K_1 L}_{\substack{\text{Carbonaceous Organic}\\ \text{Matter Oxidation}}} - \underbrace{\frac{K_4}{h}}_{\substack{\text{Sediment Oxygen}\\ \text{Demand}}} - \underbrace{\alpha_5\beta_1 N_1 - \alpha_6\beta_2 N_2}_{\text{Nitrification}}\end{aligned} \tag{3.14}$$

where C is the concentration of a constituent; A is the stream's cross-sectional area; E is the dispersion coefficient; U is the net downstream velocity; S is the source or sink; K_2 is the reaeration rate; α_3 is the photosynthesis oxygen production rate; μ is the algae growth rate; α_4 is the respiration oxygen consumption rate; BM is the biomass concentration; ρ is the algae respiration rate; K_1 is the oxygen removal rate; L is the biochemical oxygen demand; K_4 is the sediment oxygen demand rate; h is the river depth; α_5 is the oxygen uptake per unit of ammonia oxidized; β_1 is the biological ammonia oxidation rate; N_1 is the ammonia concentration; α_6 is the oxygen uptake per unit of nitrite oxidized; β_2 is the biological nitrite oxidation rate; and N_2 is the nitrite concentration.

Constraints (3.10)–(3.12) are included to guarantee appropriate concentrations of total nitrogen, total phosphorus, and Kjeldahl nitrogen, respectively.

3.4.5. Nonnegativity and Integrality Constraints

Finally, the nonnegativity and integrality constraints specify the domain for the various decision variables of the model

$$x_{(i,j)}, y_{(i,j)} \in \{0,1\}, \ \forall (i,j) \in \mathbf{S} \tag{3.15}$$

$$z_{kp} \in \{0,1\}, \ \forall k \in \mathbf{N}_T, p \in \mathbf{T} \tag{3.17}$$

$$Q_{(i,j)}, E_{(i,j)}, Q\text{min}_{(i,j)}, Q\text{max}_{(i,j)} \geq 0, \ \forall (i,j) \in \mathbf{S} \tag{3.18}$$

$$QT_k \geq 0, \ \forall k \in \mathbf{N}_T \tag{3.19}$$

$$\mathrm{DO}_r, \mathrm{N}_r, \mathrm{P}_r, \mathrm{Nkj}_r \geq 0, \ \forall r \in \mathbf{R} \tag{3.20}$$

3.4.6. Model Size

The model comprises $(1+T)N_T+6S+4R$ decision variables, of which $2S+\mathrm{T}N_T$ are binary, and $N+2N_T+S+4R+1$ constraints (where S, N, N_T, T, and R represent the cardinality of sets **S**, **N**, $\mathbf{N}_T$, **T** and **R**, respectively).

3.5. Solution method

For solving the mixed-integer nonlinear optimization model presented in the preceding section, we implemented a simulation annealing (SA) algorithm. This type of local search algorithm is inspired on the physical annealing of metals, and was first used for optimization purposes by Kirkpatrick et al. (1983) and Cerny (1985). We decided to use this type of algorithm because SA proved to be extremely efficient on water network design and public facility planning models previously dealt with by some authors (Cunha and Sousa 1999, 2001, Antunes and Peeters 2001, Nunes et al. 2004, 2006).

The main ingredients of the SA algorithm used to solve the model are summarized in Figure 3.1. The algorithm starts from some initial feasible solution, which is designated as the current solution. Then, a candidate solution is selected in the neighborhood of the current solution. For each candidate solution, the hydraulic model is used to size the sewers, the possible pump stations, and the treatment plants, and the water quality model is used to verify the environmental constraints. The level of the different water quality parameters is determined and compared with the limits they must verify. If these limits are exceeded the solution is rejected. If not, the candidate solution becomes the current solution according to the Metropolis criterion; that is, with probability given by $p = \min\{1, \exp(-\Delta C/\theta)\}$, where ΔC is the difference between the cost of the candidate solution and the cost of the current solution and θ is a parameter called temperature, which, in an SA context, is used to control the search procedure. Therefore, the candidate solution becomes the current solution if its cost is smaller than the cost of the current solution. Otherwise, if it is not, the probability that it will become the current solution increases as the difference of cost between the solutions decreases, and, also, as the temperature decreases. This operation is repeated when decreasing temperature in a controlled manner until the cost of solutions ceases to decrease.

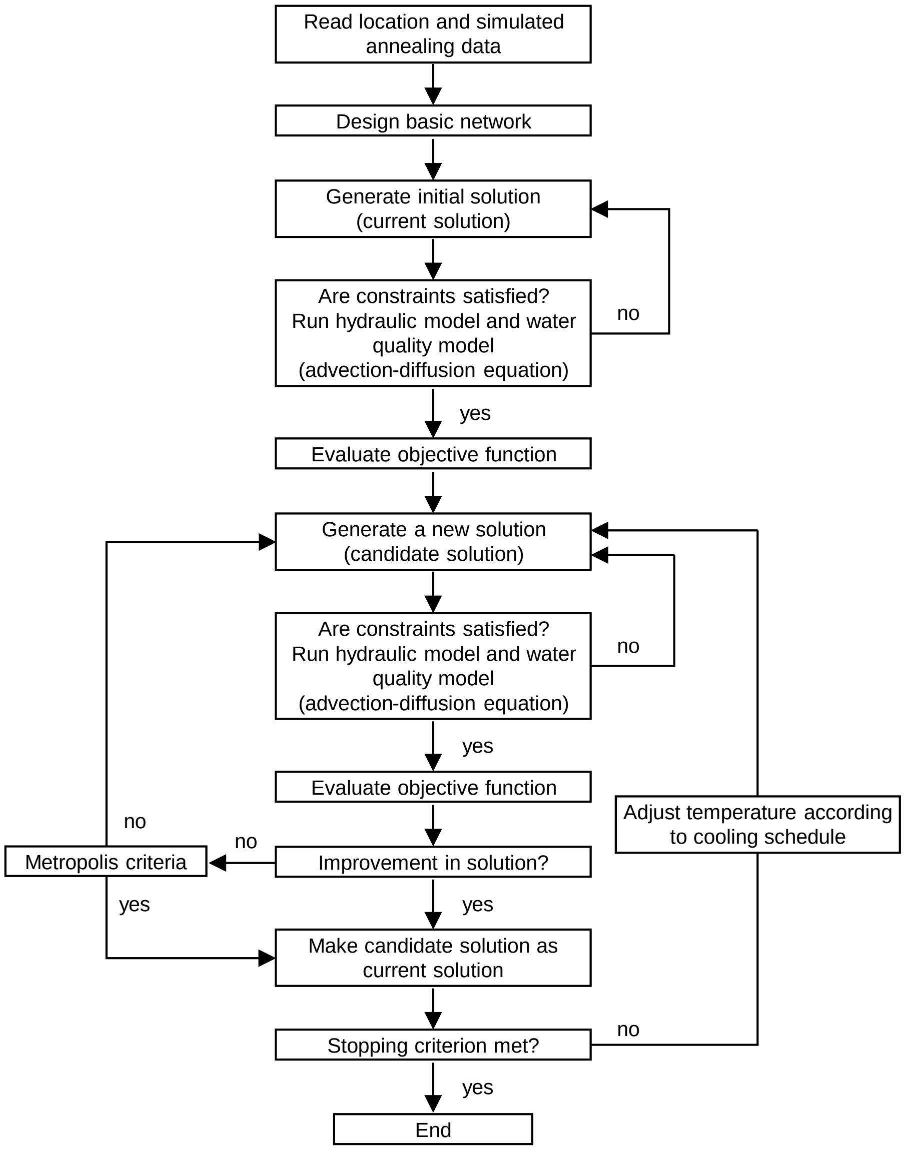


Figure 3.1 - Flowchart for the simulated annealing algorithm

The three main aspects involved in the implementation of an SA algorithm are: definition of the initial solution; definition of the neighborhood of a current solution; and definition of the cooling schedule (initial temperature, temperature decrease rate, and final temperature). In our implementation, the initial solution is defined installing treatment plants at every treatment node and connecting the population centers to the closest treatment node. The neighborhood of a current solution consists of every solution that can be reached by selecting a sewer and replacing its downstream node with one of the nodes adjacent to the upstream node. The cooling schedule was defined with four parameters, α_1, λ, γ, and σ, as proposed in Johnson et al. (1989). Parameter α_1 sets the initial acceptance rate for candidate solutions with cost 10% larger than the cost of the current solution (it also sets the initial temperature, because, given the Metropolis criterion, $\theta_1 = -0.1\times C_1/\ln \alpha_1$, where C_1 is the cost of the initial solution). Parameter λ sets the minimum number of candidate solutions which must be evaluated at each temperature (if after $\lambda \times S$ evaluations, where S is the number of possible sewers, the minimum cost or the average cost did not decrease then the temperature decreases). Parameter γ sets the rate at which the temperature decreases. Finally, parameter σ sets the maximum number of temperature decreases that may occur without an improvement of the minimum or the average cost. When this number is reached, the search stops.

The calibration of the SA parameters was made through a "smart" trial-and-error procedure for a large sample of test problems designed to mimic real-world problems. The calibration procedure and the test problems are described in detail in Zeferino et al. (2006). The best values identified for the SA parameters were as follows: $\alpha_1 = 0.3$; $\lambda = 30$; $\gamma = 0.3$; and $\sigma = 8$.

3.6. Case studies

In order to illustrate the type of results that can be obtained through the application of the model presented previously, we applied it to three case studies—hereafter designated as Case 1, Case 2, and Case 3. The regions under planning have the same size in the three cases (48.4 km × 28.0 km) and are crossed by rivers with the same hydraulic and environmental characteristics. The number of population centers is 38 for the three case studies, and they have the same locations and sizes (Figure 3.2). However, the topography of the regions varies from relatively flat to rather hilly (Figure 3.3). The possible locations for treatment plants coincide with sites S1–S8. There are two types of treatment plants: small (for populations up to 10,000) and large. The limit concentration for the water quality parameters were set at typical values: 7.0 mg/L for dissolved oxygen (DO); 7.5 mg/L for total nitrogen (N); 1.0 mg/L for total phosphorous (P); and 3.0 mg/L for Kjeldahl nitrogen (Nkj).

The model has been applied to the three case studies considering the following scenarios: (1) no constraints on water quality; (2) constraints on DO, N, and P, considered individually; (3) simultaneous constraints on DO, N, and P; and (4) simultaneous consideration of all environmental constraints (including Nkj).

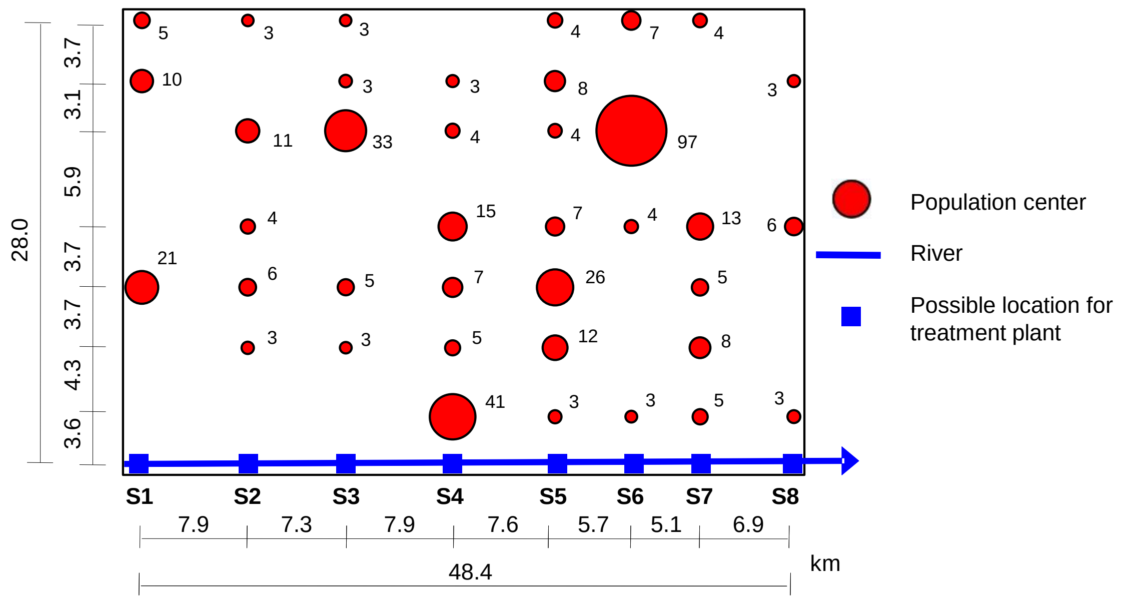
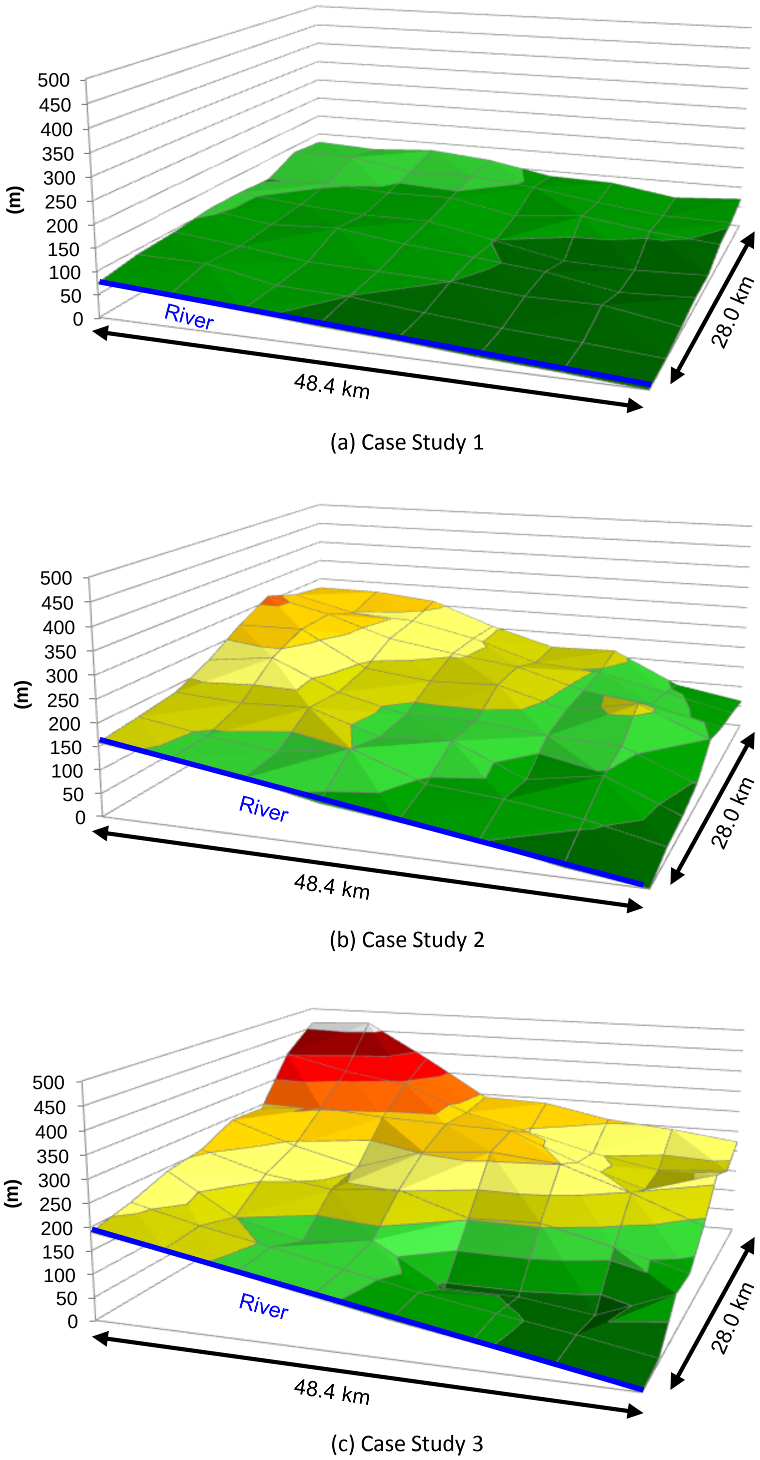


Figure 3.2 - Spatial distribution of population and possible location for treatment plants (values close to population centers indicate population in thousands)



(a) Case Study 1

(b) Case Study 2

(c) Case Study 3

Figure 3.3 - Topography for the three case studies

For solving the model we used *OptWastewater*, a user-friendly Visual Basic program developed at the University of Coimbra to run under Windows XP (Chapter 8). Each case study was solved for 10 different random seeds. As one could expect as SA is a random search algorithm, the results obtained for the ten seeds were not always the same—some solutions were better than others. But the solution values were rather similar, as indicated by coefficients of variation typically inferior to 1.0%. If new seeds were used, it would not be impossible to find a better solution. However, this did not happen when we solved Case 1 for 40 additional random seeds and the various types of constraints on water quality. The evolution of the values of current solutions and best solutions through time, as well as the evolution of temperature, followed the pattern typically encountered when an SA algorithm is applied (Figure 3.4). Initially, current solutions change considerably, as well as their value. As the algorithm proceeds, the temperature decreases, the number of good current solutions tends to increase, and the number of poor solutions tends to decrease. The shape of the curve depicting the evolution of current solution values becomes progressively less irregular and, eventually, becomes flat. This means that the current solution remains unchanged and coincides with the best solution. The time taken to solve the case studies on an Intel Core 2 Duo 2.66 GHz computer with 3 GB of random access memory ranged between 30 and 60 min. This is a very acceptable computing effort considering the size of the case studies and the complexity of the model.

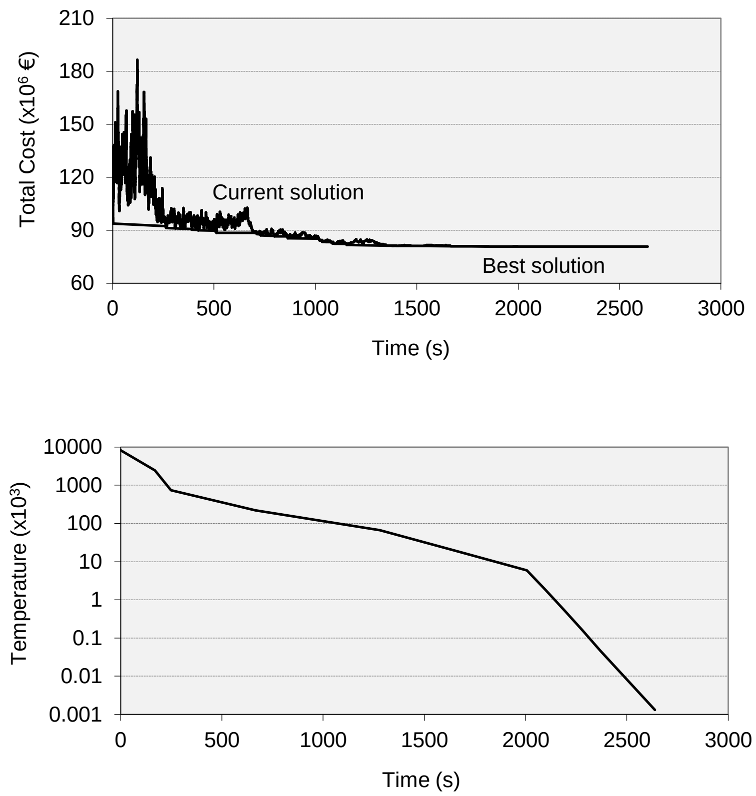


Figure 3.4 - Evolution of current and best solution values and temperature (logarithmic scale) during a run of the simulated annealing algorithm

The costs corresponding to the best solutions obtained for the three case studies are presented in Table 3.2. As expected, the lowest total costs occur when no constraints on water quality are considered. The costs are higher for Case 1 (79.97 M€) than for Cases 2 and 3 (75.79 and 77.16 M€, respectively). The separate presence of DO, N, or P constraints leads to small (or no) total cost increases. Instead, the simultaneous presence of the three constraints, especially if combined with the presence of constraints on Nkj, can raise costs very significantly. This is particularly evident for Case 3, where total costs increase 23.0%, whereas they only increase 2.6 and 16.3% for Cases 1 and 2. Table 3.2 also provides information on the three cost components taken into account—

sewer networks, pump stations, and treatment plants. For Case 1, sewer network costs do not change significantly as water quality constraints are added. But this is not the case with the other case studies when the four constraints are considered simultaneously. Pump station costs decrease as water quality constraints are added in Case 1, whereas the opposite occurs for the other case studies. Treatment plant costs increase, in general, for the three case studies as water quality constraints are added, especially in Case 3. Further information on the interplay between total costs, the various types of costs, and the different water quality parameters can be found in Chapter 5.

Table 3.2 - Cost of solutions as a function of the environmental constraints being considered

	Solution costs (M€)											
	Case Study 1				Case Study 2				Case Study 3			
Environmental constraints	Sewer network	Pump stations	Treatment plants	Total	Sewer network	Pump stations	Treatment plants	Total	Sewer network	Pump stations	Treatment plants	Total
No	39.76	2.50	37.70	79.97	36.96	1.49	37.34	75.79	36.82	2.54	37.81	77.16
P < 1.0 mg/l	39.76	2.50	37.70	79.97	37.03	0.88	40.25	78.16	36.82	2.54	37.81	77.16
DO > 7.0 mg/l	41.32	1.77	37.70	80.79	36.91	1.40	40.70	79.00	36.26	1.54	42.77	80.57
N < 7.5 mg/l	38.80	1.91	40.66	81.36	36.97	0.76	42.76	80.49	36.86	2.74	41.41	81.01
DO + N + P	39.05	2.00	40.66	81.71	36.62	1.40	44.93	82.94	34.46	1.99	46.47	82.92
DO + N + P + Nkj	38.12	0.96	42.94	82.02	42.49	2.86	42.76	88.11	43.09	5.70	46.15	94.94

The wastewater system solutions obtained for the three case studies when controlling for dissolved oxygen constraints only or for all environmental constraints are depicted in Figure 3.5. For Case 1, when only DO constraints are considered, most wastewater is sent to a single large treatment plant (the rest is sent to two small treatment plants) through a network that fully exploits the topography of the region, with sewers being set up mostly along valleys. When all environmental constraints are considered, wastewater has to be split among two large treatment plants to avoid excessive concentration of pollutants at a single location. For Case 3, two large treatments are built even when only DO constraints are considered, but now this happens to reduce the need to pump wastewater. Indeed, only four pump stations are included in the wastewater system corresponding to this case study, against eight pump stations in Case 1. Again for Case 3, when all the environmental constraints are considered, three large treatment plants are built, to further disperse pollutants. As a general rule, solutions take advantage of topography, locating the treatment plants downstream if the environmental constraints are not violated. When water quality requirements become more severe, some treatment plants are located upstream to make it possible to fulfill the environmental constraints.

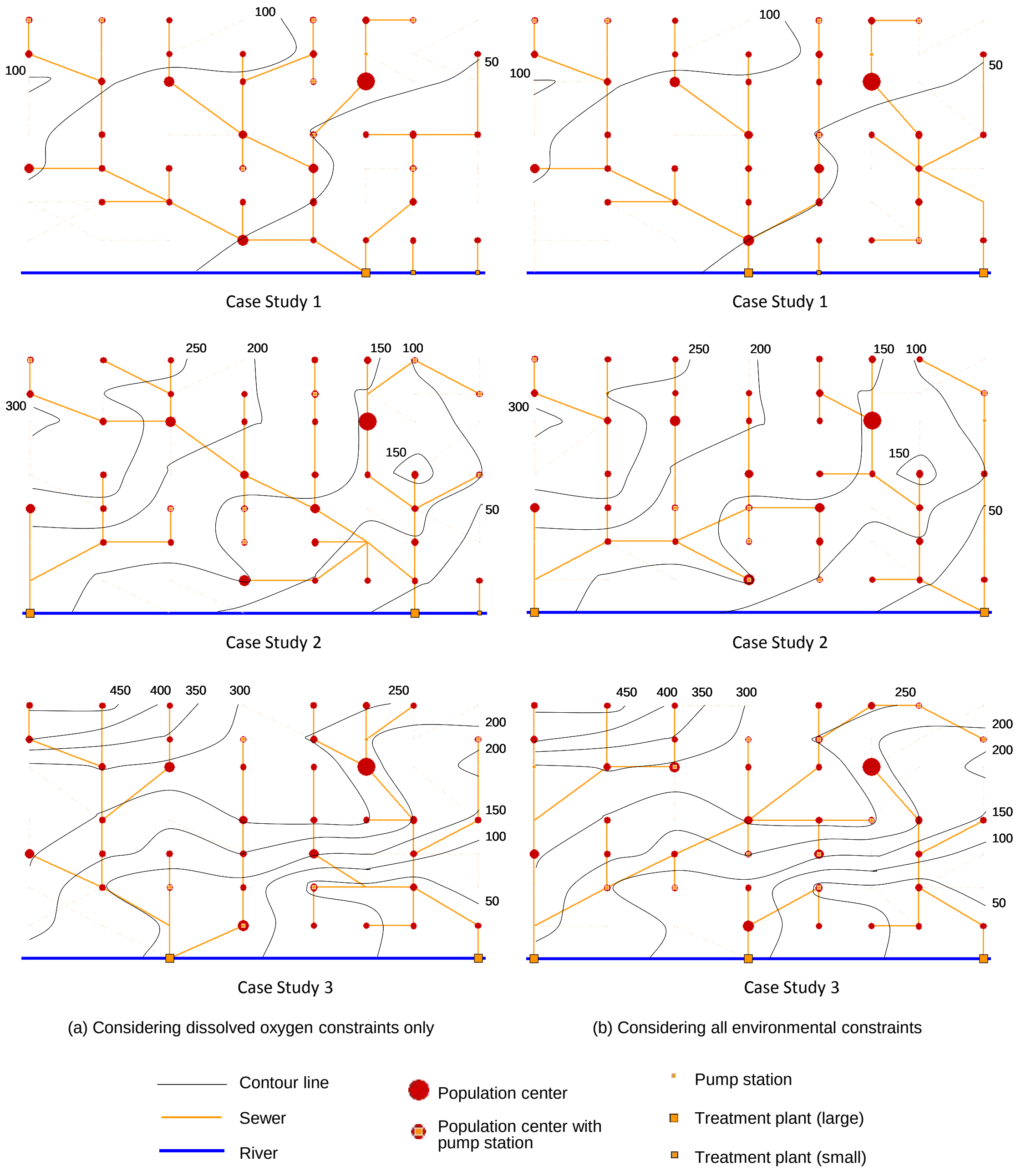
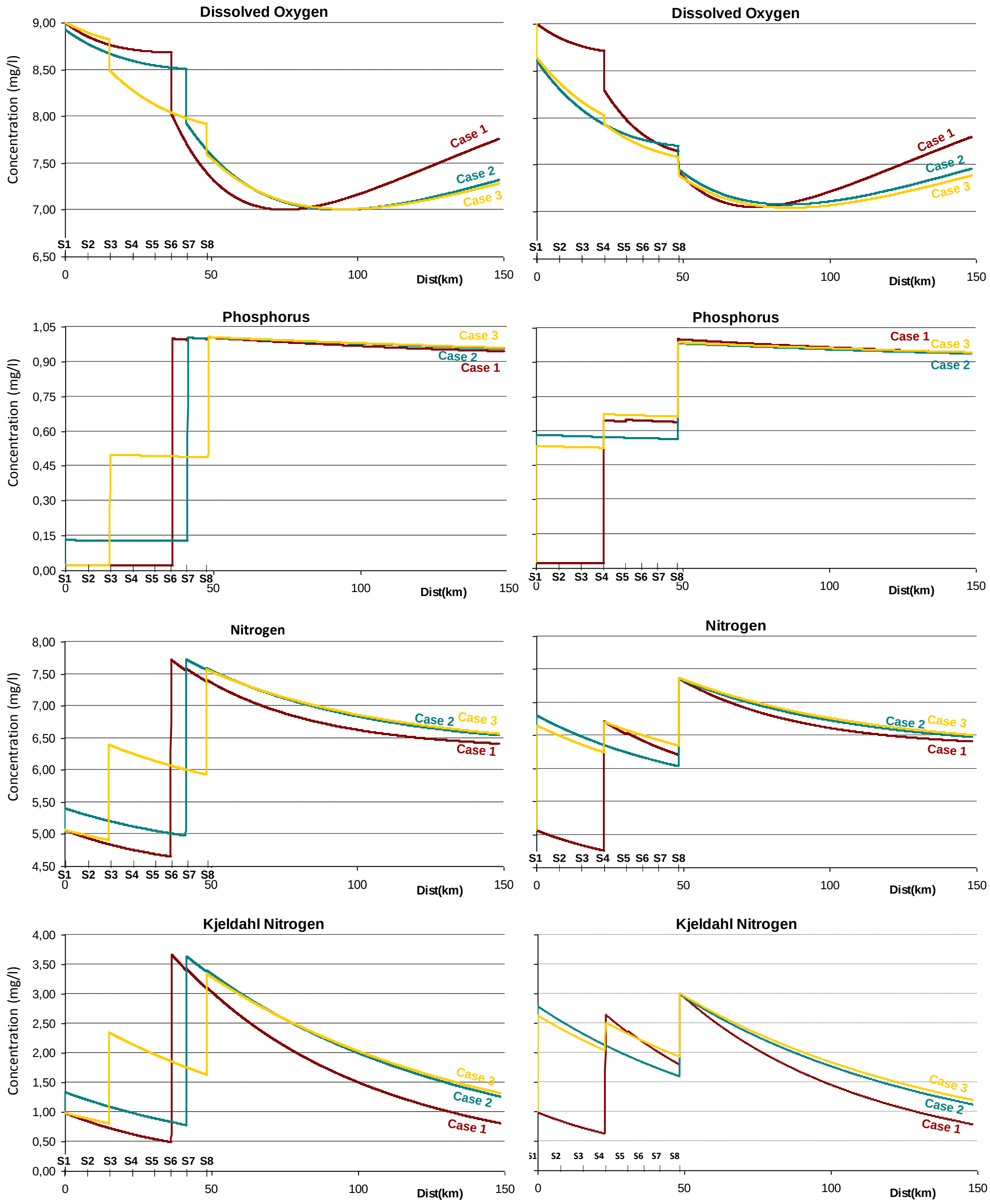


Figure 3.5 - Solutions of the three case studies

The *OptWastewater* program also provides information on pollutant concentrations along the river, up to a distance of 100 km from the last section of the river in the region under study. This is exemplified in Figure 3.6. Figure 3.6 shows the concentration curves for the basic water quality parameters (dissolved oxygen, total nitrogen, total phosphorus, and Kjeldahl nitrogen) when controlling for dissolved oxygen constraints only or for all environmental constraints. The curves for dissolved oxygen have the typical shape of oxygen sag curves, with the minimum (less favorable) values appearing approximately 25 km after the location of the last treatment plant. The effect of including each new treatment plant is expressed through the steps of the curves.

In specific situations, one may desire to keep the concentration of additional water quality parameters (namely biochemical oxygen demand, phytoplankton, nitrate, nitrite, ammonia, organic nitrogen, inorganic phosphorus, and organic phosphorus) within given limits. If this was the case, the optimization model would have to be augmented with the corresponding constraints. The new constraints could be handled with only minor changes to the existing solution algorithm because the main calculations needed are already being made to determine the concentration of DO, N, and P.



(a) Considering dissolved oxygen constraints only

(b) Considering all environmental constraints

Figure 3.6 - Evolution of the basic water quality parameters along the river

3.7. Conclusion

In this chapter, we presented an optimization model for regional wastewater systems planning, as well as the heuristic method developed for solving the model. The model is aimed at helping to determine the best possible configuration for the wastewater system of a region taking economic, environmental, and technical criteria explicitly into account. The hydraulic behavior of the sewer network and the quality dynamics of river waters are handled through detailed simulation models. The heuristic method used for solving the model combines a simulated annealing algorithm with a local search procedure. The model can be used separately or as a building block of a large decision-support tool designed to cover all (or most of) the issues involved in the implementation of an Integrated Water Resources Management approach. The European Union recently adopted this approach with the purpose of achieving the goal of good water status in 2015.

The usefulness of the model was demonstrated for three case studies, in the presence of various combinations of environmental constraints. Indeed, despite the significant amount of problems to be solved (38 population centers), the model was always able to provide credible solutions to the case studies within very reasonable computing effort (less than an hour on a top-market personal computer). The results obtained for the case studies made clear that the presence of some environmental constraints, in some circumstances, may have a large impact on solution costs. This is an important aspect decision makers must take into account in the definition of a sustainable water resources management policy.

Chapter 4

An efficient simulated annealing algorithm for regional wastewater system planning

4.1. Introduction

One of the greatest challenges the world faces today is related to the goal of providing a very significant part of the planet's population with access to drinking water and basic sanitation. This fact is widely recognized by the United Nations and explains why that goal was included among the Millennium Development Goals (UN 2005). To achieve it, the UN recently launched the Water for Life action through the World Health Organization (WHO 2005). By means of this action, the UN is aiming to halve the number of people without access to basic sanitation by the year 2015. Today, this population amounts to 2,600 million (40% of the total world population). In the long term, the benefits derived from the accomplishment of this objective, mainly by reducing disease and increasing productivity, will largely exceed the costs (by approximately eight times). However, in the short run, a very significant investment effort—estimated at 11.3 billion USD per year—is required.

The problems targeted by the Water for Life action are mainly felt in developing countries, and especially in Sub-Saharan Africa and Eastern Asia, where at most only 40% of the population was provided with basic sanitation in 2002. But there are also problems to overcome in developed countries. For instance, in 2002, despite the progress achieved through the application of *Directive 91/271/CEE* (modified by *Directive 98/15/CE*), 25 of the 556 European Union cities with population over 150,000 did not treat their wastewater. Moreover, in a further 158 of those cities, wastewater treatment was considered to be inadequate (EC 2004). Most of these cities were located in Southern Europe and Great Britain. The largest ones were Barcelona and Milan. Among the cities where wastewater was not treated, four were located in areas classified as highly sensitive from the environmental standpoint: Alginet (Spain), Barreiro (Portugal), Pepinster (Belgium), and Waterford (Republic of Ireland).

Planning solutions for wastewater system problems are often sought at a local level—that is, each city develops its own solution. However, in many cases, it would be possible to find better solutions from both the economic and the environmental viewpoints if they were looked for at a regional level.

The search for the best regional wastewater systems can only be efficient if pursued through an optimization model, because the number of options available is far too large to enable individual evaluation. To represent the problems to be solved as accurately as possible, the model must incorporate discrete variables (for the possible locations of treatment plants and the commercial diameters of sewers, for example) and nonlinear functions (for the hydraulic behavior of wastewater systems, for example). That is, it is necessary to resort to a discrete nonlinear optimization model. Even for small-scale instances, models of this type can be extremely difficult to solve. In general, they must be handled through heuristic algorithms. Since the 1980s, numerous heuristic algorithms (e.g., genetic algorithms, tabu search, neural networks, and simulated annealing) have been successfully developed to determine optimum (or near-optimum) solutions to complex civil engineering models (Adeli and Cheng 1994, Savic and Walters 1997, Jiang and Adeli 2008). In particular, simulated annealing (SA) algorithms have been applied with remarkable results to several hydraulic system planning models (Cunha and Sousa 1999, Dougherty and Marryott 1991, McCormick and Powell 2004, Monem and Namdarian 2005).

In this chapter, we present a study recently carried out to design an efficient SA algorithm for regional wastewater system planning (RWSP). The study fits into a line of research within which an integrated approach to RWSP is being developed (Cunha et al. 2004, 2005, Sousa et al. 2002). The main innovations in relation to our previous work concern the parameters of the SA algorithm. Like many other modern heuristic algorithms, SA algorithms involve parameters that must be calibrated for the specific instances they are applied to. Often, the calibration is performed through some trial-and-error procedure. For complex models like the ones involved in RWSP, this can be an arduous task and lead to unreliable results. Instead, we have used a particle swarm (PS) algorithm—which is itself a modern heuristic algorithm—to calculate optimum (or near-optimum) values for the SA parameters within reasonable computing time. A large set of test instances designed to replicate real-world problems was subjected to calculation. Based on the results obtained for the test instances, we established general expressions for the optimum values of the SA parameters as a function of their geographic and environmental characteristics. Through the application of these expressions, one can determine the value of the parameters to be used when addressing real-world problems without having to go through the arduous, unreliable trial-and-error procedure that otherwise would have to be performed.

The chapter is organized as follows. We start by recalling the model developed to represent the RWSP problem. Then, we describe the SA algorithm used to solve it and the procedure used to determine general expressions for the optimum value of its parameters. Also, we analyze the quality of the solutions provided by the model and the computing time required to obtain them. Next, we exemplify the type of results that can be obtained with the model through the SA algorithm. In the final section, we summarize the content of the study presented in this chapter and indicate some directions for future research.

4.2. Planning model

The study reported in this chapter is based on the RWSP model presented in Sousa et al. (2002) and described in Chapter 3. This model was developed to deal with the problem of finding the minimum-cost configuration for the system needed to drain the wastewater generated by the population centers (wastewater sources) of a region. The components of the system are: one or more sewer networks to connect the population centers with the receiving water bodies; and treatment plants to process wastewater before sending it to the receiving water bodies. The sewer network(s) may include pump stations to lift wastewater if it is unfeasible or uneconomic to drain it by gravity. The system must comply with all relevant regulations. In particular, it must ensure that the wastewater discharged from each treatment plant will not exceed a given maximum amount, consistent with the water quality standards defined for the receiving water body.

The formulation of the RWSP model is as follows:

$$\text{Min} \sum_{i \in N_S \cup N_I} \sum_{j \in N} C_{ij}\left(Q_{ij}, L_{ij}, x_{ij}\right) + \sum_{k \in N_T} \sum_{p \in T} C_{kp}\left(QT_k, y_{kp}\right) \tag{4.1}$$

subject to

$$\sum_{j \in N_S \cup N_I} Q_{ji} - \sum_{j \in N} Q_{ij} = -QR_i, \quad i \in N_S \tag{4.2}$$

$$\sum_{j \in N_S \cup N_I} Q_{jl} - \sum_{j \in N} Q_{lj} = 0, \quad l \in N_I \tag{4.3}$$

$$\sum_{j \in N_S \cup N_I} Q_{jk} = QT_k, \quad k \in N_T \tag{4.4}$$

$$\sum_{i \in N_S} QR_i = \sum_{k \in N_T} QT_k \tag{4.5}$$

$$\sum_{p \in T} y_{kp} \leq 1, \quad k \in N_T \tag{4.6}$$

$$Q\min_{ij} . x_{ij} \leq Q_{ij} \leq Q\max_{ij} . x_{ij}, \quad i \in N_S \cup N_I ; j \in N \tag{4.7}$$

$$QT_k \leq \sum_{p \in T} QT\max_{kp} . y_{kp}, \quad k \in N_T \tag{4.8}$$

$$x_{ij} \in \{0,1\}, \quad i \in N_S \cup N_I ; j \in N \tag{4.9}$$

$$y_{kp} \in \{0,1\}, \quad k \in N_T\,;\, p \in T \tag{4.10}$$

$$QT_k \geq 0, \quad k \in N_T \tag{4.11}$$

$$Q_{ij} \geq 0, \quad i \in N_S \cup N_I\,;\, j \in N \tag{4.12}$$

where $\boldsymbol{N}$ is set of nodes (population centers plus possible intermediate nodes plus possible treatment plants); $\boldsymbol{N_S}$ is set of population centers; $\boldsymbol{N_I}$ is set of possible intermediate nodes; $\boldsymbol{N_T}$ is set of possible treatment plants; $\boldsymbol{T}$ is set of treatment plant types; C_{ij} is discounted costs for installing, operating, and maintaining a sewer linking node i to node j; Q_{ij} is flow carried from node i to node j; L_{ij} is length of the sewer linking node i to node j; C_{kp} is discounted costs for installing, operating, and maintaining a treatment plant of type p at node k; QT_k is amount of wastewater conveyed to a treatment plant located at node k; QR_i is amount of wastewater produced at node i; $Q\min_{ij}$ and $Q\max_{ij}$ are minimum and maximum flow allowed in the sewer linking node i to node j, respectively; $QT\max_{kp}$ is maximum amount of wastewater that may be treated at node k with a treatment plant of type p; x_{ij} is binary variable that is equal to one if there is a sewer to carry wastewater from node i to node j, and is equal to zero otherwise; and y_{kp} is binary variable that is equal to one if there is a treatment plant of type p at node k, and is equal to zero otherwise.

The objective-function (4.1) of this discrete nonlinear optimization model expresses the minimization of the total discounted costs for installing, operating, and maintaining sewer networks and treatment plants. The first term corresponds to sewer network costs, which depend on the wastewater flow (thus, on the diameter of sewers), on the length of sewers, and on the hydraulic heads at the extremities of sewers. They include the costs incurred to install, operate, and maintain the pump stations needed to lift wastewater from low-head to high-head points. The second term corresponds to treatment plant costs, which, for a given type of treatment plant, depend on the amount of wastewater treated there. Constraints (4.2), (4.3), and (4.4) are the continuity equations for three types of network nodes: population centers, possible intermediate nodes, and possible treatment plants. Intermediate nodes may be necessary to allow an appropriate representation of topography and/or the early regrouping of sewers. Constraint (4.5) ensures that all the wastewater generated by the population centers in the region will be treated. Constraint (4.6) guarantees that there will be at most one treatment plant, of a specific type, in each treatment node. Constraint (4.7) ensures that the flow carried by sewers will be within given minimum and maximum values. These values depend on both the diameter and slope of sewers, and on flow velocity requirements. The hydraulic calculations needed to determine the diameter and slope of sewers are based on the well-known Manning equation. Constraint (4.8) ensures that the wastewater sent to any treatment plant will not exceed given maximum values. These values depend on the quality standards defined for the receiving water bodies and vary with the type of treatment plant. Constraints (4.9) and (4.10) are zero-one constraints, and constraints (4.11) and (4.12) are nonnegativity constraints.

4.3. Simulated annealing

4.3.1. General algorithm

The method designed to solve the RWSP model consists of an SA algorithm enhanced with a local improvement (LI) algorithm (Dowsland 1993, Kirkpatrick et al. 1983). We decided to use neighborhood search methods rather than population search methods (e.g., genetic algorithms) because they involve fewer solution changes from iteration to iteration, thus making it easier to preserve solution feasibility throughout the search process.

The basic steps of the algorithm are identified in Figure 4.1. It starts from some initial incumbent solution. Then, a candidate solution is selected at random in the neighborhood of the incumbent solution. The candidate solution becomes the incumbent solution with probability p given by the Boltzmann–Gibbs distribution; that is, $p = \min\{1, \exp(\Delta V/t)\}$, where ΔV is the difference between the value of the incumbent solution and the value of the candidate solution, and t is a parameter called temperature in an SA context. Therefore, the candidate solution becomes the incumbent solution if its value exceeds the value of the incumbent solution. Otherwise, if it does not, the probability that it becomes the incumbent solution increases as the difference in value between the solutions decreases, and, also, as the temperature decreases. This operation is repeated while lowering the temperature in a controlled manner until the value of solutions ceases to increase. The LI algorithm starts with the best solution identified through the SA algorithm as the incumbent solution and, in successive iterations, moves into the best solution in the neighborhood of the incumbent solution if its value exceeds the value of the incumbent solution.

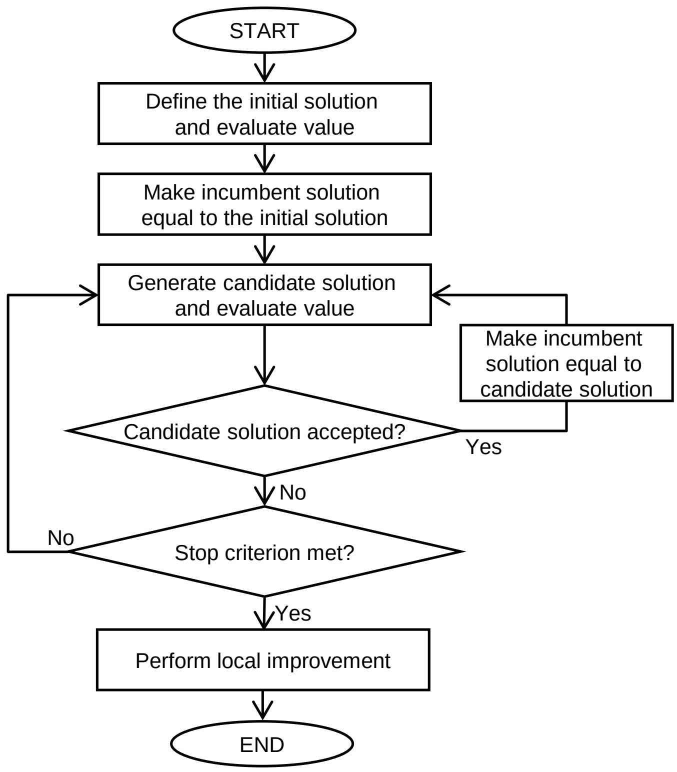


Figure 4.1 - Basic steps of an annealing algorithm

4.3.2. Implementation for the RWSP problem

The three main aspects involved in the implementation of an SA algorithm are: definition of the initial incumbent solution, definition of the neighborhood of an incumbent solution, and definition of the cooling schedule (initial temperature, temperature decrease rate, and final temperature). For the RWSP model, these aspects were handled as follows. The initial incumbent solution is defined by installing treatment plants at every treatment node and connecting the population centers to the closest treatment node, as shown in Figure 4.2. The neighborhood of an incumbent solution consists of every solution that can be reached by selecting a sewer and replacing its downstream node with one of the nodes adjacent to the upstream node, as shown in Figure 4.3. In this figure, starting from the incumbent solution, two possible candidate solutions are represented. In one of them, sewer *a* was selected and replaced by *a'*, leading to a major change of the network. In the other, sewer *b* was selected and replaced by *b'*, entailing only a minor change of the network. The cooling schedule was defined with four parameters, α_1, λ, γ, and σ, as proposed in Johnson et al. (1991). Parameter α_1 is the initial acceptance rate for candidate solutions with value 10% worse than the value of the initial solution, V_0. It allows the determination of the initial value of temperature, t_1. Indeed, as $p = \min\{1, \exp(\Delta V/t)\}$, $\alpha_1 = \exp(-0.1\ V_0/t_1)$, and $t_1 = -0.1\ V_0/\ln\alpha_1$. Parameter λ defines the minimum number of candidate solutions that must be evaluated at each temperature (if after $\lambda \times S$ evaluations, where S is the number of possible sewers, the best solution value, V^*, or the average solution value, m_V, does not improve, the temperature decreases). Parameter γ sets the rate at which the temperature decreases. Finally, parameter σ establishes the maximum number of temperature decreases that may occur without an improvement of the best or the average solution value. The way the parameters interact is described in Figure 4.4.

The aptitude of SA algorithms to find optimum or near-optimum solutions within acceptable computing time largely depends on the way they are implemented for the particular model to be solved. In particular, it depends on the way the values of their parameters are calibrated. In the next section we describe the procedure carried out to calibrate the parameters of the SA algorithm developed for the RWSP model.

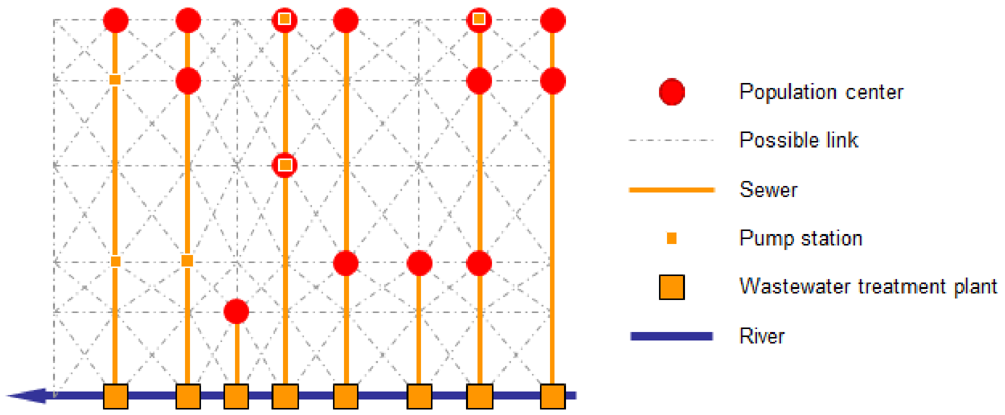


Figure 4.2 - Initial solution for the annealing algorithm

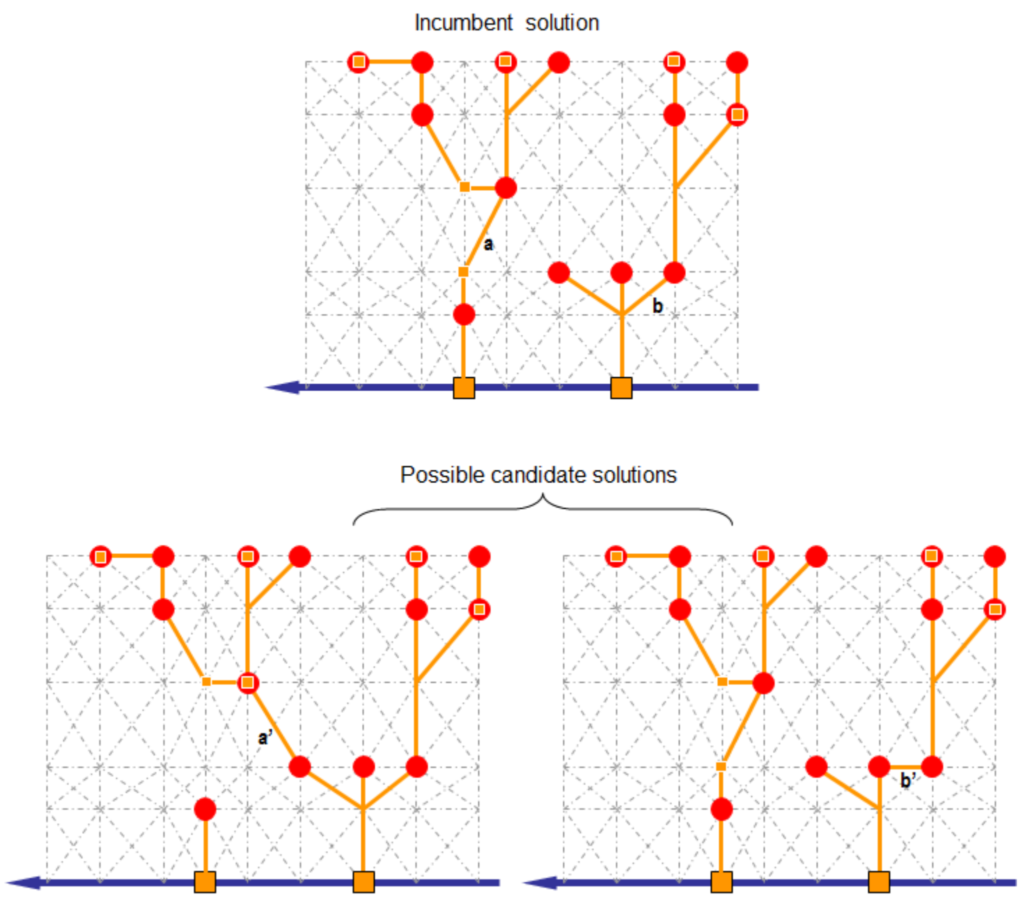


Figure 4.3 - Neighborhood of an incumbent solution

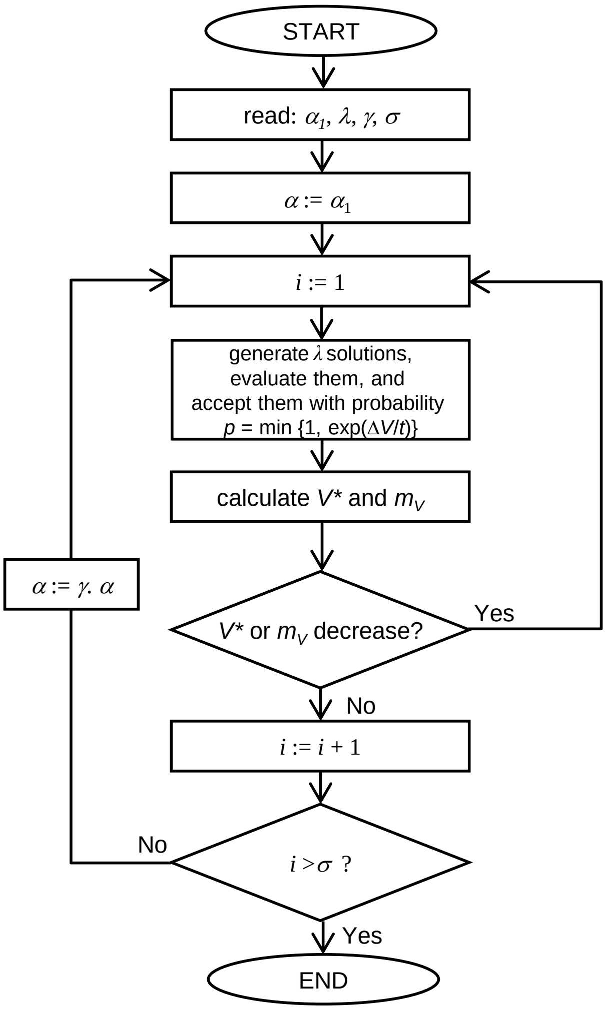


Figure 4.4 - Cooling schedule for the annealing algorithm

4.4. Parameter calibration

As stated in the introductory section, the main innovations of the work reported in this chapter are related to the parameters of the SA algorithm. Our objective is to determine general expressions for the optimum value of the parameters of the SA algorithm as a function of the geographic and environmental characteristics of the RWSP problem to be solved. Several tasks were undertaken to achieve this. First, we generated a large set of test instances designed to replicate real-world problems. Next, we developed a PS algorithm to determine optimum (or near-optimum) parameter values for each test instance. Then, using multiple regression analysis, we established general expressions for the optimum value of each parameter as a function of both the characteristics of the test instances and the values of other parameters. Finally, we analyzed the quality of the solutions obtained for the test instances by applying the SA algorithm with parameters of values given by the general expressions calculated before, as well as the time required to compute them. Below, we provide information on each of these tasks.

4.4.1. Test instances

The test instances were generated according to partly random rules for the shape and topography of the planning regions, the location and size of their population centers, the configuration of sewer networks, and the possible location and maximum discharge for treatment plants.

4.4.1.1. Shape and topography of the regions

The regions have a rectangular shape, with the length of each side randomly chosen, in terms of a uniform distribution, in the interval [20, 40] km. The bottom of the rectangle corresponds to a river that receives the wastewater generated by the population centers in the region. The topography of the region is based on a grid. The distance between two consecutive axes of the grid is a value randomly chosen in the interval [3, 6] km (given the length of the sides of the region this means that the grid will have from 4 to 13 axes in each direction). Heights at the nodes of the grid vary between a value of zero in the left bottom corner (river mouth) and a value randomly chosen in the interval [100, 500] m. From the mouth of the river, heights vary along each axis proportionally to a value randomly chosen in the interval $[-3, 6]$ units. To guarantee a single value for the height in each node, a weight, G, randomly chosen in the interval [20, 80]% is applied to the variation of heights parallel to the river, and a weight of $(100 - G)\%$ is applied to the variation of heights perpendicular to the river. The dominant orientation of the ridges is the direction (parallel or perpendicular to the river) that receives the larger weight. The height along the river increases proportionally to a value randomly chosen in the interval [1, 2] units.

4.4.1.2. Location and size of population centers

Population centers are located in a percentage of the nodes of the grid (not coincident with the river) randomly chosen in the interval [25, 75]%. The total population of the region is calculated by multiplying the number of centers with a value randomly chosen in the interval [5,000, 15,000]. The population is distributed across centers in the following way: the population of the second-largest center is equal to the population of the largest center divided by a value randomly chosen in the interval [1.5, 2.5]; the population of the third-largest center is the population of the largest center divided by a value randomly chosen in the interval [2.5, 3.5]; and so forth. Thus, the expected population distribution across centers follows a law frequently observed in real-world situations: Zipf's law (Brakman et al. 2001).

4.4.1.3. Configuration of sewer networks

Sewer networks connect population centers to treatment plants, either directly or indirectly, through other population centers or intermediate nodes. Each node must be connected to one, and only one, of the adjacent nodes (i.e., the closest nodes in directions parallel, perpendicular, and diagonal to the river).

4.4.1.4. Possible location and maximum discharge at treatment plants

Treatment plants can be set up in any treatment node (i.e., node of the river). The maximum discharge in each plant (defined to guarantee the quality standards that must be met in the river) is obtained through the division of the total volume of wastewater generated in the population centers of the region by a value randomly chosen in the [0.0, 3.0] interval. If this value is less than 1.0, it may be enough to set up one treatment plant; if it is greater than 2.0 it will be necessary to install at least three treatment plants.

4.4.1.5. Other data

Other data (e.g., the wastewater generation rates and the costs of the components of wastewater systems) were taken from a sample of Portuguese case studies.

4.4.1.6. Application examples

To illustrate the kind of test instances obtained through the application of the rules described above, three examples—Test Instances 1, 2, and 3—are displayed in Figure 4.5. The characteristics of the three instances with regard to number of nodes, percentage of population centers in relation to the number of nodes, total population, land roughness, ridge orientation, and maximum percentage of wastewater discharge in a treatment plant in relation to total wastewater discharge are summarized in Table 4.1. Land roughness is the number of times the slope changes from negative to positive and *vice versa* in the nodes of the grid multiplied by the maximum height of the region and divided by twice the number of nodes (the reason for dividing by twice the number of nodes is because in each node the slope can change both parallel and perpendicular to the river). Ridge orientation is the average angle formed between the direction of the ridges and the perpendicular to the river, measured in grades.

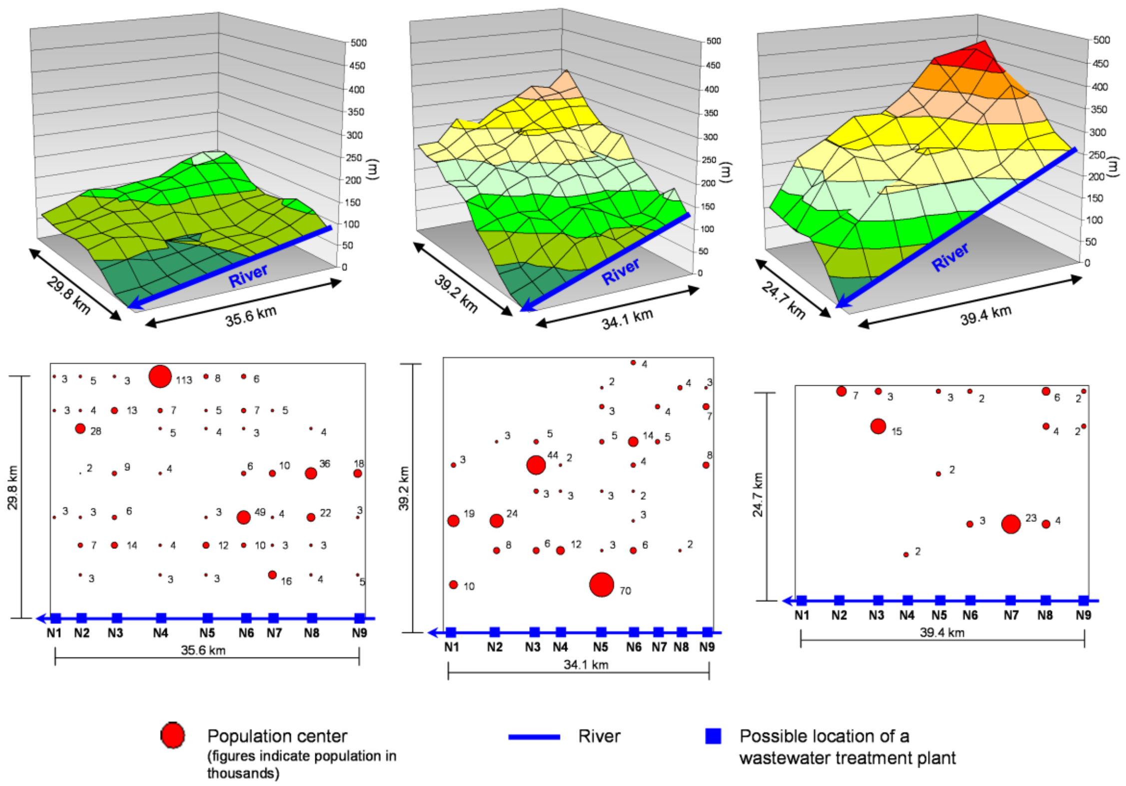


Figure 4.5 - Shape and topography (top), and location and size of population centers (bottom) for Test Instances 1 (left), 2 (center), and 3 (right).

Table 4.1 - Characteristics of the Test Instances 1, 2 and 3

Problem characteristics	Test Instance		
	1	2	3
Number of nodes	72.0	99.0	54.0
Percentage of population centers (in relation to the number of nodes)	73.0	36.0	31.0
Population of the region (thousands)	487.7	293.4	77.0
Land roughness (meters)	66.6	112.6	155.5
Ridge orientation (grades)	66.0	41.0	53.0
Maximum percentage of wastewater discharge in a treatment plant (in relation to total wastewater discharge)	100.0	45.5	83.3

4.4.2. Particle swarm algorithm

The solutions obtained through an SA algorithm depend on the values of the parameters of the algorithm, as well as on random effects (as SA is a randomized algorithm). For choosing those values, trial-and-error calibration procedures are often used despite being very time-consuming. But it is also possible to choose them through an optimization approach: the aim is to determine values for the parameters that maximize the value of the solution (i.e., in the case of this chapter, minimize the total costs of the wastewater system).

For the calibration of the parameters, we decided to apply an optimization approach. More specifically, we used a PS algorithm (see Kennedy and Eberhart 1995 and, for a very detailed presentation of the algorithm and its properties, Parsopoulos and Vrahatis 2002). This (quite new) type of modern heuristic algorithm is inspired by the way the members of a swarm synchronize their movements to achieve some objective. We decided to apply this type of algorithm because it appeared to us to be especially well suited to determine the optimum values of parameters expected to vary together.

A PS algorithm consists of the following steps. First, a population (swarm) of solutions, $\boldsymbol{S}$, is generated. Each solution (particle) is characterized by a position P in $\boldsymbol{D}$-dimensional space, with some value in terms of a given objective, and a velocity, V. The velocity is the rate at which the position changes. Then, in successive iterations, each solution changes position at a velocity that depends on its previous velocity, on the best position it has previously taken (P^*_{sd}), and on the best overall position taken by any of the solutions (P^*_{gd}). The procedure ends when, after several iterations, the change of the position taken by the solutions becomes very small (i.e., velocity becomes close to zero). The expressions used to calculate the velocity and the position of a solution $s \in \boldsymbol{S}$ in the dimension $d \in \boldsymbol{D}$, in iteration i, are:

$$V_{sd}^{i} = a \times V_{sd}^{i-1} + b \times \left(P_{sd}^{*} - P_{sd}^{i-1}\right) + b \times \left(P_{gd}^{*} - P_{sd}^{i-1}\right) \tag{4.13}$$

$$P_{sd}^{i} = P_{sd}^{i-1} + V_{sd}^{i} \tag{4.14}$$

where a and b are parameters.

In our implementation of the PS algorithm, each solution comprised four dimensions, the SA parameters α_1, λ, γ, and σ. According to the suggestions given in Trelea (2003), the size of the population was set at 15, and PS parameters a and b were set at 0.729 and 0.747. The number of iterations was set at 15, because for this number of iterations the velocity of each particle was already very close to zero. The initial values of the SA parameters (i.e., the initial positions of the solutions) were randomly chosen in the following (wide) intervals: α_1 in [0.1, 0.9]; λ in [1, 80]; γ in [0.1, 0.9]; and σ in [1, 20]. The initial velocity of the solutions was randomly chosen within ±1/10 of the range of each parameter.

The way PS algorithms perform is illustrated in Figure 4.6 with results from Test Instance 1. The top image shows the evolution of the values of the 15 solutions. Over the 15 iterations, these values converge progressively to 88.2 M€ (except for one of the solutions). The bottom image displays the evolution of the values of the SA parameters. They oscillate considerably within their range of variation in the initial iterations, before becoming fairly stable after 10 iterations.

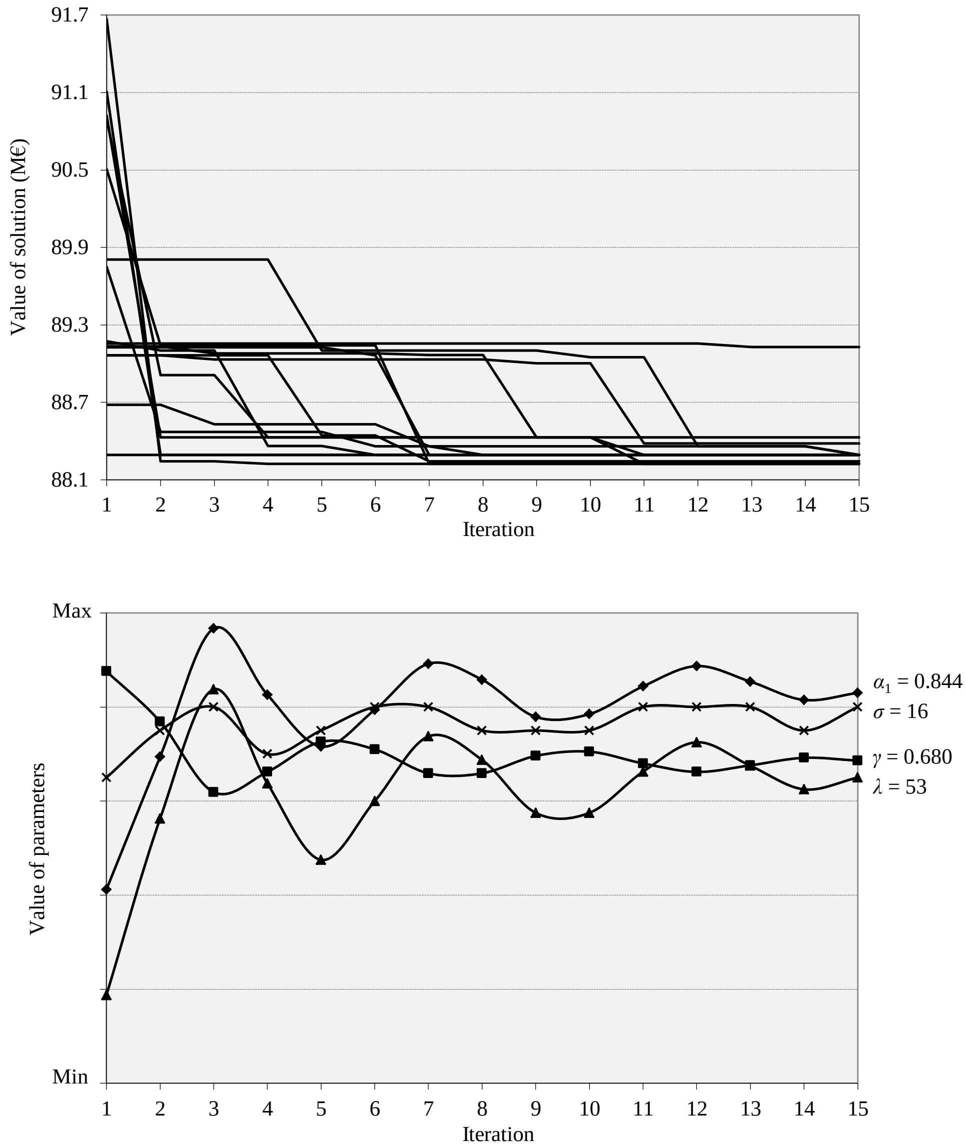


Figure 4.6 - Evolution of solution values (top) and SA parameter values (bottom) during the execution of the particle swarm algorithm for Test Instance 1.

4.4.3. General expressions for optimum SA parameters

The determination of general expressions for the optimum (or near-optimum) values of the SA parameters as a function of problem characteristics cannot be made simply by performing a multiple regression analysis on the parameter values against the problem's characteristics. Indeed, the value of each parameter can, in principle, be influenced by the values taken by some other parameters.

4.4.3.1. Cross-influences between SA parameters

To detect possible cross-influences between SA parameters, we first used multiple regression analysis to study the relationship between the values of the solutions given by the SA algorithm and the values of the parameters. The study employed a quadratic regression model for a set of 20 test instances. Each instance was solved with 50 sets of parameters and five random seeds. The values of the parameters were randomly chosen in the same intervals as before; that is: α_1 in [0.1, 0.9], λ in [1, 80], γ in [0.1, 0.9], and σ in [1, 20].

A quadratic regression model has the following general form:

$$\begin{aligned} V = {} & a_1 \times \alpha_1^2 + a_2 \times \lambda^2 + a_3 \times \gamma^2 + a_4 \times \sigma^2 + a_5 \times \alpha_1 \times \lambda + a_6 \times \alpha_1 \times \gamma + a_7 \times \alpha_1 \times \sigma \\ & + a_8 \times \lambda \times \gamma + a_9 \times \lambda \times \sigma + a_{10} \times \gamma \times \sigma + a_{11} \times \alpha_1 + a_{12} \times \lambda + a_{13} \times \gamma + a_{14} \times \sigma \end{aligned} \tag{4.15}$$

where V is value of the solution (cost of the wastewater system); $a_1, \ldots, a_{14}$ are model coefficients.

This model was used because it is the simplest model that permits the detection of cross-influences of parameter values on solution values. For instance, if V is differentiated with respect to α_1, one gets

$$\partial V / \partial \alpha_1 = 2 \times a_1 \times \alpha_1 + a_5 \times \lambda + a_6 \times \gamma + a_7 \times \sigma + a_{11}$$

Therefore, if a_5, a_6, or a_7 are (significantly) different from zero, the influence of parameter α_1 on V is linearly dependent on another parameter (λ, γ, or σ).

When applied to the 20 test instances (one at a time), the model was always able to capture the influence of parameter values on solution values with great accuracy. Indeed, the adjusted correlation coefficient for the model was always larger than 0.98. The *t*-tests performed on the coefficients of the model revealed that, with regard to the product terms, only the coefficients for $\alpha_1 \times \sigma$ and $\gamma \times \sigma$ were, in most cases, significantly different from zero for the 95% and, especially, the 99% confidence intervals (Table 4.2). This clearly indicates that the values used for σ have a strong influence on the values to be used for parameters α_1 and γ.

Table 4.2 - Cross-influence between SA parameters

Model term	Number of times model coefficients were significantly different from zero	
	Confidence 95%	Confidence 99%
$\alpha_1 \times \lambda$	7	3
$\alpha_1 \times \gamma$	7	4
$\alpha_1 \times \sigma$	12	8
$\lambda \times \gamma$	6	4
$\lambda \times \sigma$	5	2
$\gamma \times \sigma$	13	11

4.4.3.2. Relationship between SA parameters and problem characteristics

Based on the previous results, general expressions for the optimum values of the SA parameters as a function of problem characteristics were determined for a set of 50 test instances with a multiple regression model of the following general form:

$$\xi = a_1 \times N + a_2 \times U + a_3 \times P + a_4 \times R + a_5 \times G + a_6 \times W + a_7 \times \sigma \tag{4.16}$$

where ξ is value of SA parameter; N is number of nodes; U is percentage of population centers (in relation to the number of nodes); P is total population (thousands); R is land roughness (meters); G is ridge orientation (grades); W is maximum percentage of wastewater discharge in a treatment plant (in relation to total wastewater discharge); and $a_1, \ldots, a_7$ are model coefficients.

The dependent variables (ξ) considered for the analysis were the values of the α_1, λ, and γ parameters obtained with three different seeds through the PS algorithm. Initially, σ entered as an independent variable because of our results for the cross-influences between SA parameter values and solution values. However, we found that the regression coefficients a_7 were never significantly different from zero. Hence, we also calibrated the regression model for σ.

The general expressions obtained for the parameters were as follows:

$$\alpha_1 = 0.003327 \times N + 0.005151 \times G \tag{4.17}$$

$$\lambda = 0.586190 \times N + 0.617798 \times U - 0.058433 \times P \tag{4.18}$$

$$\gamma = 0.005743 \times U + 0.003282 \times W \tag{4.19}$$

$$\sigma = 0.092615 \times U + 0.078216 \times G + 0.040662 \times W \tag{4.20}$$

These expressions were obtained after eliminating the variables for which the model coefficients were not significantly different from zero through (backward) stepwise regression analysis (Draper and Smith 1998). They describe the optimum values of the parameters as a function of problem characteristics very accurately. Indeed, the adjusted correlation coefficient for the SA parameters was always larger than 0.88.

According to the expressions above, the optimum value to be used for α_1 depends on the number of nodes and ridge orientation. The larger the number of nodes, the larger α_1 should be. Also, the more ridges are parallel to the river, the larger α_1 should be (this could be expected because ridges parallel to the river tend to make the configuration of the wastewater system more complex). The number of nodes also influences the value to be used for λ, and ridge orientation also influences the value to be used for σ. The percentage of population centers in relation to the number of nodes (i.e., population dispersion) influences the optimum values to be used for λ, γ, and σ. The maximum percentage of wastewater discharge in a treatment plant in relation to total wastewater discharge influences γ and σ. As one could expect, all these influences are positive. The only negative influence is associated with total population, which, for a given number of nodes and a given percentage of population centers, makes λ decrease. A possible explanation for this is that, in these conditions, the sizes of population centers will differ more, thus making the structure of the problems better defined and their solutions easier to determine. It should be noticed here that land roughness was never retained as an explanatory variable for the optimum value of the parameters.

4.4.4. Quality of solutions

Assessment of the quality of the solutions given by the SA algorithm (with parameters calculated by the PS algorithm) involved two stages. First, we compared their value with the optimum solution value obtained through complete enumeration for a set of 20 small test instances (i.e., instances of size 5 × 5 with each node possibly connected to the closest nodes only in the directions parallel and perpendicular to the river, which was the largest size for which we were able to determine optimum solution). For these instances, the SA algorithm was always capable of finding the exact optimum solution in a couple of seconds, against an average of approximately 4 hours with complete enumeration. Second, we analyzed the solutions given by the SA algorithm for the 50 test instances on 10 runs, each run corresponding to a different random seed. The results of the analysis are summarized in Figure 4.7. For 23 of the 50 instances, the average solution for the 10 runs was within 0.5% of the best solution found (which may or may not be the exact optimum solution). Conversely, it was at more than 1.5% of the best solution in only six instances. The difference between the best and the worst solution was less than 1.5% for 22 of the 50 instances, and never exceeded 6.0%. For two of the instances, the best solution was the same in the 10 runs. In conclusion, it can be said that the solutions provided by the SA algorithm are generally quite good and fairly stable. However, for large instances, in some rare cases, they can clearly miss the optimum. For this reason, when dealing with large real-world problems (which, in most cases, can be represented with enough detail using, say, 100 nodes), it is advisable to run the SA algorithm several times, with several random seeds, before choosing the solution to implement in practice.

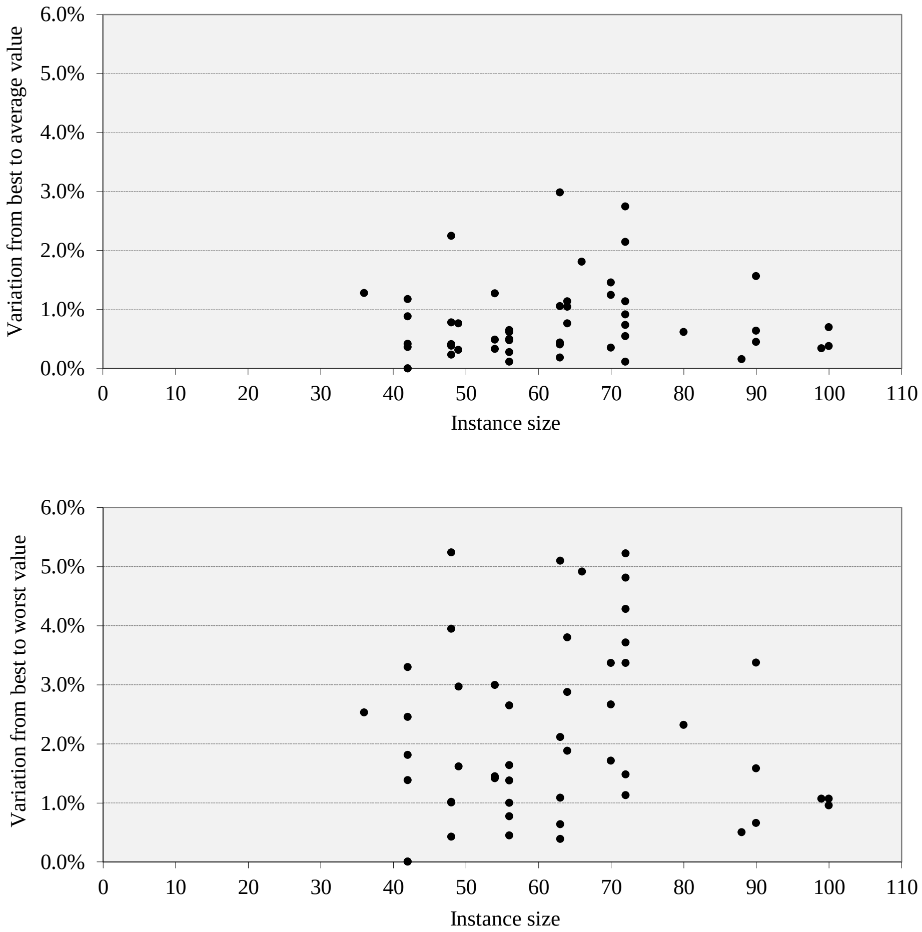


Figure 4.7 - Variation from best to average (top) and worst (bottom) solution value as a function of instance size.

4.4.5. Computing time

As one could expect, the time required by the computation of solutions varied significantly with the size of the test instances (as measured by the number of grid nodes). The average computing time for the smallest instances (sizes up to 60 nodes) was less than 100 seconds except in one case (Figure 4.8). The largest instances (sizes larger than 80 nodes) always took an average of less than 700 seconds. In general, computing time increased with instance size. The coefficient of variation of computing time over the 10 runs was quite small—less than 15% for 39 of the 50 instances and never more than 30%. To sum up, it can be said that the SA algorithm can provide solutions within quite reasonable and very stable computing time even for large real-world problems.

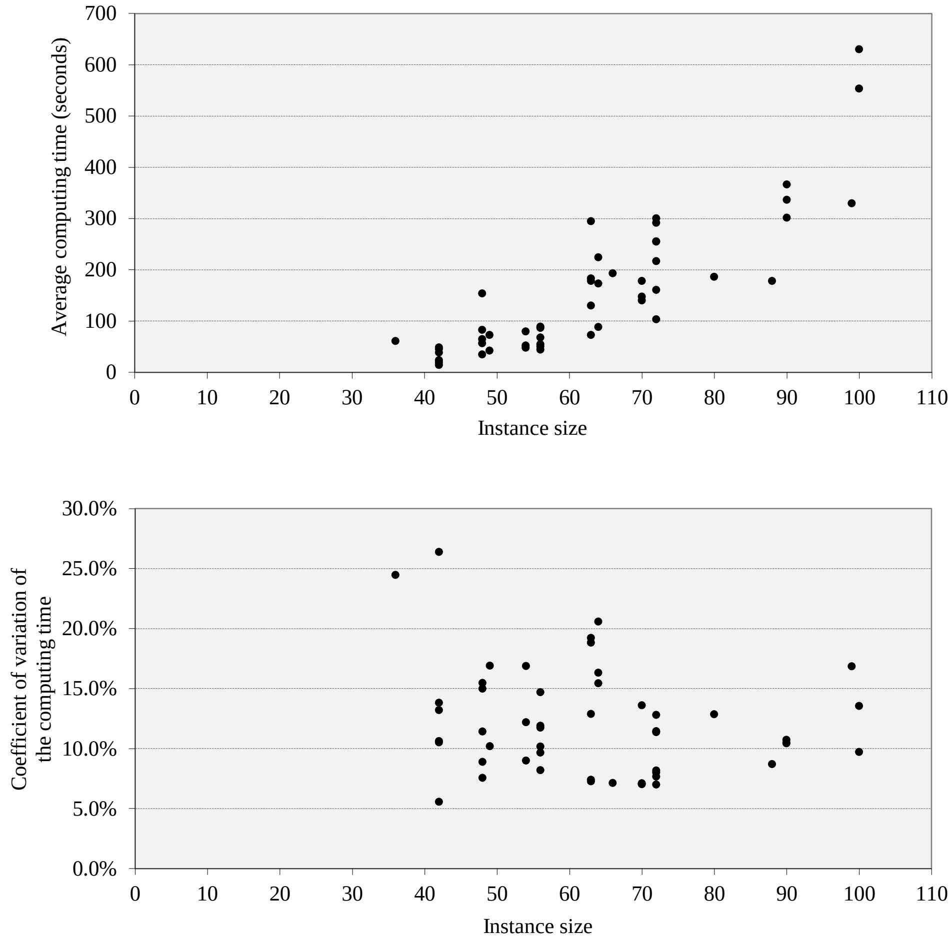


Figure 4.8 - Average computing time (top) and coefficient of variation of computing time (bottom) as a function of instance size (number of nodes).

4.5. Model results

The results that can be obtained through the application of the RWSP model are exemplified in Table 4.3 and Figure 4.9. These results correspond to Test Instances 1, 2, and 3. The geographic and environmental characteristics of these instances are given in

Figure 4.5 and Table 4.1. In absolute terms, as one might expect, total costs increase as the number of population centers and the figure for total population increase. This happens, in the first place, because the length of sewer networks increases (as well as the diameter of sewers). In relative terms, Test Instance 1 has the lowest treatment costs because it requires only one treatment plant, thus allowing economies of scale to be made. Test Instance 2 requires three wastewater treatment plants. Treatment plant costs are the highest (in relative terms), whereas sewer network and pump station costs are the lowest. Test Instance 3 entails the smallest number of pump stations but the highest pump station costs, because it involves a hilly region. However, Test Instance 1, which corresponds to a flatter region than the region of Test Instance 2, entails pump station costs higher than those of Test Instance 2. This happens for two main reasons. First, the ridges in Test Instance 1 run more parallel to the river than in Test Instance 2. Second, because three treatment plants are required in Test Instance 2, ridge crossing can be easily avoided by installing sewer networks along valleys.

Table 4.3 - Results for Test Instances 1, 2, and 3

	Sewer network			Pump stations			Wastewater treatment plants			
		Cost			Cost			Cost		
Test Instance	Length (km)	Value (M€)	% of total	Number	Value (M€)	% of total	Number	Value (M€)	% of total	Total cost (M€)
1	208.85	43.32	49.1	13	2.05	2.3	1	42.85	48.6	88.22
2	183.86	25.29	40.3	7	1.06	1.7	3	36.40	58.0	62.76
3	99.23	10.88	45.8	4	0.76	3.2	2	12.09	51.0	23.74

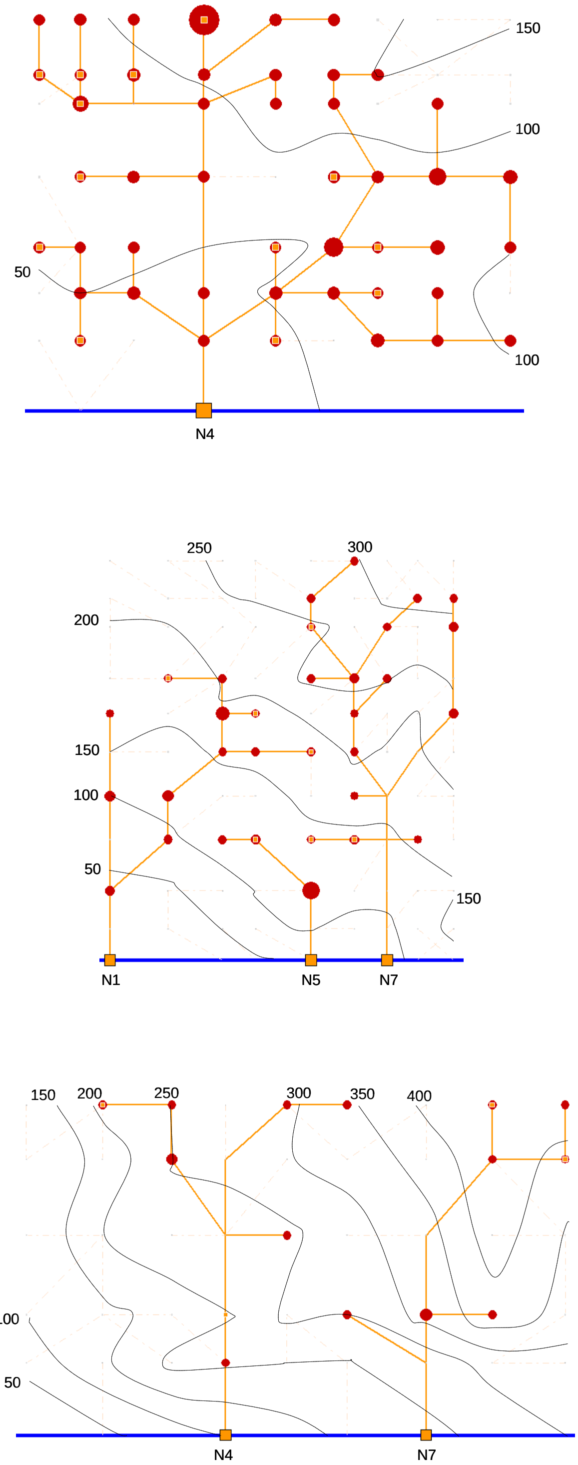


Figure 4.9 - Best solutions for Test Instances 1 (top), 2 (middle), and 3 (bottom).

4.6. Conclusion

In this chapter, we have described the development of an efficient SA algorithm for solving an RWSP model. In relation to our previous research in the area, the main innovations concern the calibration of the parameters of the algorithm. Instead of the trial-and-error procedure typically used for this purpose, we applied a PS algorithm to determine optimum or near-optimum values for the parameters of the SA algorithm, as a function of the geographic and environmental characteristics of the problems to be solved. The results obtained from applying this approach to a large set of test instances clearly indicate that, in general, it will help with finding very good quality solutions to real-world planning problems at the expense of very reasonable computing effort.

With regard to the future, we will focus more on enhancing the RWSP model than on enhancing the SA algorithm (which is already quite sophisticated). Indeed, the model can be improved with respect to a number of important aspects, including the consideration of several objectives and uncertainty issues. Once these improvements are made, the parameters of the algorithm will have to be recalculated. This will be relatively easy to do using the PS algorithm presented in this chapter.

Chapter 5

Multi-objective model for regional wastewater systems planning

5.1. Introduction

Water is essential for all forms of life, but, when polluted, it can be harmful to ecosystems in general and human beings in particular. Concerns with the pollution caused by the disposal of wastewater go back to approximately 3000 BC, when the first wastewater systems were built. However, it was just in the last two centuries, with the expansion of urbanization, that wastewater systems became essential components of developed urban areas.

The target of reducing by half the population without sustainable access to safe drinking water and basic sanitation by 2015 was recently established by the United Nations in their effort to fulfill the Millennium Development Goals (UN 2005, WHO 2005). This target applies chiefly to the problems faced by less-developed countries, but developed countries also have serious problems related to water quality (US EPA 1998, EC 2000). In order to attenuate these problems, appropriate wastewater systems have to be built (or rebuilt) in many places of the world. Instead of, as often happens, being designed for separate cities or parts of cities, these systems should be planned at regional scale, because this would allow better economic and environmental solutions for the problems to be solved.

In this chapter, we describe a multi-objective model for regional wastewater systems planning. The model is aimed at determining an efficient solution for the layout of the sewer networks, and for the location, type, and size of the pump stations and treatment plants to be included in the systems. The planning problems posed by these types of systems have typically been addressed through optimization models with a cost-minimization objective. The other concerns involved in those problems are often handled as constraints, considering upper and/or lower limits for the values of some variables (e.g. variables representing the emission of pollutants). However, these limits may be difficult to establish, making those variables easier to be handled as objectives. If some of the objectives are conflicting, it is impossible to find solutions where they are optimized simultaneously. Through a multi-objective model, it is possible to identify solutions that are a good compromise with regard to conflicting objectives.

This chapter is organized as follows. In the next section, we provide a literature review on optimization models for wastewater systems planning, where special emphasis is given to multi-objective models. Subsequently, we expose the essential ingredients of the multi-objective model introduced in this chapter. Then, we describe the simulated annealing algorithm (SAA) used to solve the model. Afterwards, we present the three test instances used for illustrating the application of the model. Then, we describe the results obtained for the test instances with the SAA, considering different combinations of weights for the objectives. In the final section, we summarize the conclusions and indicate directions for future research.

5.2. Literature review

Optimization models for wastewater systems planning were introduced in the late 1960s. One of the main problems dealt with since then is the waste load allocation problem, i.e. (originally) finding a minimum global cost solution for the level of pollutants to remove from a stream at a number of pollutant point sources (Liebman and Lynn 1966, ReVelle et al. 1967, Burn and Lence 1992). The other main problem is the problem dealt with in this chapter, i.e. finding a minimum global cost solution for the configuration of a regional wastewater system. The first study on this subject was reported by Deininger (1966), who applied linear programming techniques to a simplified version of the problem. Other examples of early studies are due to Wanielista and Bauer (1972), Joeres et al. (1974), McConagha and Converse (1973), and Chiang and Lauria (1977), who dealt with increasingly realistic versions of the problem. The former two used mixed-integer programming techniques whereas the latter two applied heuristic algorithms. The most recent studies on this problem reported in scientific journals are, to the best of our knowledge, Wang and Jamieson (2002) and Sousa et al. (2002), who used modern heuristic algorithms to determine solutions (respectively, genetic algorithms and simulated annealing). In both cases, global cost was the objective to minimize and environmental (water quality) issues were handled through constraints.

In a world increasingly more concerned with sustainable development, wastewater system planning must consider factors other than economic. This will prevent adverse impacts not only in the present but also in the future. While minimum global cost is the usual objective used in optimization models, there are several environmental, technical, social, and cultural criteria to be taken into account. Ellis and Tang (1991) identify 20 criteria such as the size and nature of the site, community support, or the cost of operation and maintenance, which should be considered in the selection of a wastewater treatment solution. The tendency to change from single- to multi-objective approaches was shown by Lee and Wen (1996). Recent studies where lists of relevant criteria are presented include: Foxon et al. (2002), regarding the water industry; Sahely et al. (2005), regarding the urban infrastructure systems; and Balkema et al. (2002) and Palme et al. (2005), specifically regarding wastewater systems (Table 5.1).

Table 5.1 - Criteria for water system planning problems

Criteria	References				
	Lee and Wen (1996)	Balkema et al. (2002)	Foxon et al. (2002)	Sahely et al. (2005)	Palme et al. (2005)
Economic	Global cost Return on investment Water use preferences	Capital cost Operational cost Maintenance cost Affordability Cost effectiveness Labour	Capital cost Operational cost Maintenance cost Decommissioning cost Willingness to pay Affordability Financial risk exposure	Capital cost Operational cost Maintenance cost Extent of reserve funds Investment in innovation, research and development	Global cost
Environmental	Dissolved oxygen Biochemical oxygen demand Phosphorus Ammonia Total mass elimination Assimilative capacity	Water resource use Nutrients use Energy use Required land area Land fertility Biodiversity	Water resource use Land use Energy use Chemical use Material use Service provision Impact on river Impact on land Impact on air Impact on biological diversity	Water use Land use Energy use Chemical use Material use Contaminants Nutrients Sludge Green-house gas emissions	Recycling of phosphorus and nitrogen Energy quantity Energy quality Emissions to ground
Social	Equality Benefit	Acceptance Institutional requirements Expertise Stimulation of sustainable behaviour	Acceptability Risks to human health Participation and responsability Public understanding and awarness Social inclusion	Acceptability Accessibility Health and safety	Acceptance
Technical	Water demand	Adaptability Reliability Durability Maintenance required Robustness	Performance Reliability Durability Flexibility and adaptability	Reliability Resiliency Vulnerability	Reliability Working conditions

Problems involving several objectives to optimize and a large number of possible decisions to make can only be dealt with appropriately through multi-objective models. The central concept of a multi-objective model is the concept of efficient solution – i.e. a solution that cannot be improved with regard to some objective without deteriorating the level of achievement of, at least, another objective. Different methods for finding approximations to the efficient solution set (also known as Pareto set) and for selecting the 'best' efficient solution have been proposed in the literature (Cohon and Rothley 1997, Collette and Siarry 2004). The constraint method is one of the earlier methods used to find the efficient solution set. Tung (1992) and Lee and Wen (1996) contain applications of this method to wastewater systems problems (the latter used also another well-known method, called the step method). More recently, genetic/evolutionary algorithms have been successfully applied to multi-objective models by various authors (Fonseca and Fleming 1995, Coello 2000, Deb 2001). Among others, Yapo et al. (1998), Burn and Yulanti (2001), and Yandamuri et al. (2006) used this kind of algorithm to determine efficient solution sets for hydraulic and water resource multi-objective models. Another method that has been widely used to handle models of this type is the weighting method (Simonovic et al. 1992, Kuo et al. 2003). However, as far as we know, it has never been applied to wastewater systems planning problems.

5.3. Multi-objective model

This chapter fits into a line of research initiated by the authors several years ago. Up to now, we have concentrated on single-objective problems. The optimization models developed within this research line were presented in Sousa et al. (2002) and Cunha et al. (2004), and described in Chapter 3. The SAA used for solving the models was first presented by Sousa et al. (2002). An improved version of the algorithm is described in Chapter 4.

The multi-objective model for regional wastewater systems planning presented in this chapter applies to any number of objectives. However, for presentation purposes, we chose to focus on three objectives: minimization of capital costs; minimization of operating and maintenance costs; and maximization of dissolved oxygen. The first objective – capital costs – refers to the initial investment in the system, and comprises the construction and equipment costs. The second – operating (and maintenance) costs – considers the costs incurred during the lifetime of the system, consisting of the recurrent costs of the facilities and equipments, including the energy costs. The capital costs are, in general, related to the operating costs, but the relationship may be quite complex. The third – dissolved oxygen – refers to one of the main indicators of water quality, because many forms of life in water bodies can only survive in the presence of minimum levels of oxygen. Despite the number of objectives being small, they represent well the essential economic and environmental concerns involved in wastewater systems planning. Moreover, the consideration of a large number of objectives can make the interpretation of results and the analysis of trade-offs quite difficult. In real-world decision-making processes, this is an important aspect to be taken into account.

The general formulation of the multi-objective model is as follows:

$$
\begin{cases}
\text{Minimize}\, CC(x_1, x_2, ..., x_n) \\
\text{Minimize}\, CO(x_1, x_2, ..., x_n) \\
\text{Maximize}\, DO(x_1, x_2, ..., x_n)
\end{cases}
$$
$$
\begin{aligned}
&\text{s.t.} \\
&g_i(x_1, x_2, ..., x_n) \leq 0,\ i = 1,2,...,m \\
&x_j \geq 0,\ j = 1,2,...,n
\end{aligned}
\tag{5.1}
$$

where *CC* refers to capital costs; *CO* indicates operating costs; *DO* refers to dissolved oxygen; $g_i(x_j)$ are the set of constraints; and x_j refers to the set of decision variables.

The decision variables x_j and the constraints g_i of this model represent, respectively, the decisions to be made (regarding the layout of sewer networks, and the location, type, and size of pumping stations and treatment plants) and the constraints to be satisfied within a regional wastewater systems planning problem (e.g. mass conservation at the nodes of sewer networks). Here, they are not specified individually. For a detailed specification of these variables and constraints, the reader is referred to Chapters 3 and 4.

The way model (5.1) is handled depends, in the first place, on how decision-makers interfere in decision processes – they may express (articulate) preferences or not, and, if they do, they may express them *a priori*, *a posteriori*, or progressively (Marler and Arora 2004).

We assumed decision-makers to be able (and willing) to express their preferences *a priori*, through the application of weights to the objectives. Within an interactive decision-making process, these weights can change progressively as decision-makers acquire a deeper understanding of the problem they are faced with. With the weights defined for the objectives, the model can be handled through the weighting method. This method consists of converting the three objective functions of model (5.1) into the following single objective function:

$$\text{Minimize } V = w_{CC}CC' + w_{CO}CO' + w_{DO}DO' \tag{5.2}$$

where V is the solution value; w_{CC} (w_{CO}, w_{DO}) is the weight; and CC' (CO', DO') is the normalized value of objective CC (CO, DO).

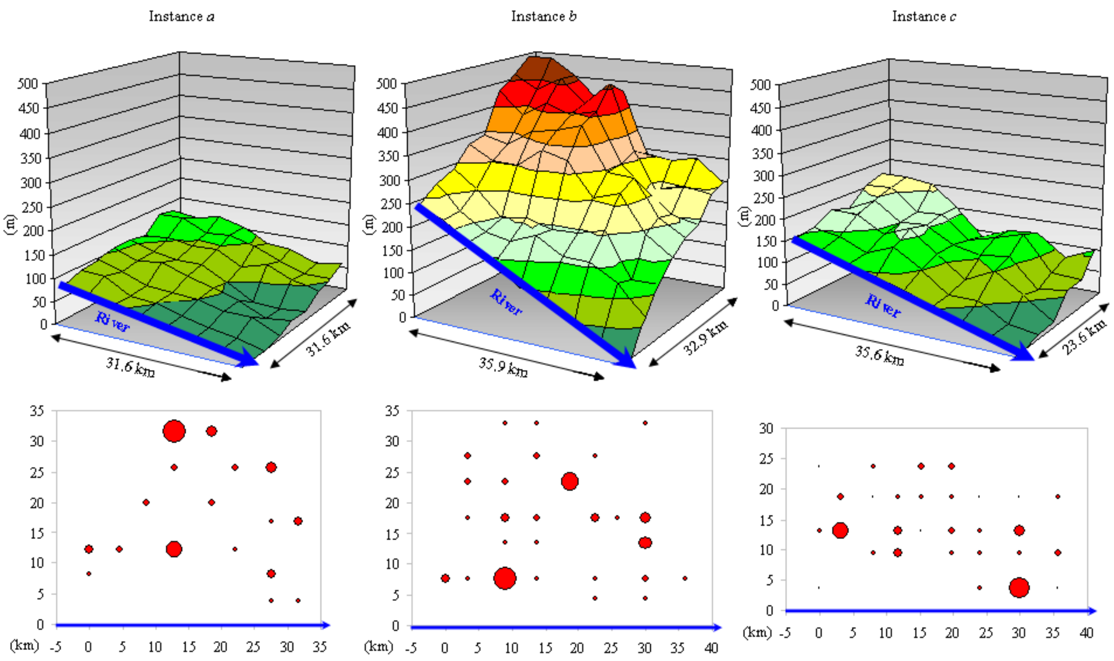
Since the value of solutions is measured in scales and units that change with the objectives, they need to be normalized. Several normalization formulae can be applied. The one we used scales the value of a solution in the range of variation of solution values (this is the best possible way of normalizing weights according to Grodzevich and Romanko (2006)). After normalization, the objective function can be written as follows:

$$V = w_{CC}\frac{\left(CC - CC^{\min}\right)}{\left(CC^{\max} - CC^{\min}\right)} + w_{CO}\frac{\left(CO - CO^{\min}\right)}{\left(CO^{\max} - CO^{\min}\right)} + w_{DO}\frac{\left(DO^{\max} - DO\right)}{\left(DO^{\max} - DO^{\min}\right)} \tag{5.3}$$

The variables with superscripts in Equation (5.3) correspond to the maximum and minimum values obtained for each indicator: $CC^{\min}$, $CO^{\min}$, and $DO^{\max}$ are the best values obtained for the objectives when optimizing (i.e. giving a 100% weight) for capital costs, operating costs, and dissolved oxygen, respectively; $CC^{\max}$, $CO^{\max}$, and $DO^{\min}$ are the worst values obtained for the objectives when optimizing for any one of the other two objectives.

5.4. Test instances

For testing the model, we considered three instances (*a*, *b*, and *c*) designed to replicate real-world problems (Figure 5.1). They were defined according to rules regarding the shape and topography of the regions, the location and size of population centers, and the location and maximum discharge at treatment plants. These rules are explained by Chapter 4.



Instance	Area (km^2)	Maximum Altitude (m)	Total Population (10^3 inh)	Number of Urban Centers	River Flow (m^3/s)	River Slope (%)
a	1024.0	134	123.7	17	2.0	0.23
b	1188.0	496	225.2	27	3.5	0.66
c	864.0	220	328.4	29	5.0	0.41

Figure 5.1 - Geography of the three regions.

The three instances have different characteristics. Instance *b* involves the region with the largest area, the highest altitude, and the hilliest landscape. It also has the river with the highest slope. The ridges in instance *a* are predominantly oriented in the direction of the river, while in instance *c* they are mainly oriented in the perpendicular direction. With respect to the population, instance *c* has the largest total population and instance *a* has the smallest. The same occurs with the number of urban centers in relation to the number of nodes. For all three instances, the wastewater produced in the region can be treated in a single treatment plant, but there can be more than one if this is advantageous from the economic or the environmental point of view. The flow of the river is the highest in instance *c* and the lowest in instance *a* (i.e. the larger river flows occur in the more populated regions).

5.5. Simulated annealing

For solving the model, we developed an SAA. This type of heuristic algorithm has already been applied successfully to various hydraulic engineering and water resources planning problems (e.g. Dougherty and Marryott 1991, Cunha and Sousa 1999, Kuo et al. 2001). An SAA is an algorithm that reproduces the annealing process in metallurgy (Kirkpatrick et al. 1983, Dowsland 1993). This process consists of heating a piece of metal and then slowly cooling it until it reaches a stable, low-energy state. An SAA starts with some initial current solution, and progressively changes it until achieving a good-quality solution (a low-cost solution in a cost-minimization problem). New solutions better than the current solution are always accepted (becoming the current solution), whereas new solutions worse than the current solution may or may not be accepted. This is important because this helps the algorithm in avoiding getting stuck at local minima. The transition between solutions is regulated by a parameter called temperature, which decreases slowly as the SAA proceeds. The probability of accepting a worse solution is inversely dependent on the solution deterioration and directly dependent on the current temperature.

The method by which temperature is changed is given by the cooling schedule. For our implementation of the SAA we used a cooling schedule defined by four parameters: α_1, λ, γ, and σ (Johnson et al. 1989). Parameter α_1 defines the initial temperature; parameter λ defines the minimum number of solutions to be evaluated at each temperature; parameter γ defines the rate at which temperature decreases; and parameter σ defines the number of temperature decreases that can occur without an improvement of the solution.

The SAA algorithm requires the use of accurate parameters, which is essential for finding good-quality solutions (Sousa et al. 2002). For the three instances considered, the parameters were calibrated using the procedure described in Chapter 4. The following parameter values were obtained:

– instance *a*: α_1 = 0.599, λ = 49, γ = 0.500, and σ = 13,

– instance *b*: α_1 = 0.497, λ = 56, γ = 0.575, and σ = 12,

– instance *c*: α_1 = 0.308, λ = 52, γ = 0.696, and σ = 12.

5.6. Application procedure

The application of the multi-objective model involved three stages. First, we determined the extreme values for the three objective variables. This was performed by using three single objective functions: minimize *CC*; minimize *CO*; and maximize *DO*. As SAA is a random search algorithm, 10 different pseudo-random number generator seeds were used for each of the three instances. The results obtained for *CC*, *CO*, and *DO* are given in Table 5.2. The values for CC^{min}, CO^{min}, and DO^{max} are in the diagonal of the matrices. This was expected, since the diagonal corresponds to the values obtained when a 100% weight is given to the *CC*, *CO*, and *DO* objectives, respectively. The values for CC^{max}, CO^{max}, and DO^{min} are also taken from the matrices. For example, in instance a, CC^{min} = 23.234 M€ and CC^{max} = 37.634 M€ (which is obtained when a 100% weight is given to the *DO* objective).

Table 5.2 - Results obtained for the three instances considering the objectives separately

Variable	Objective		
	Minimize capital cost	Minimize operating cost	Maximize dissolved oxygen
Instance *a*			
CC (M€)	23.234	24.604	37.634
CO (M€/y)	0.749	0.733	1.032
DO (mg/L)	6.088	6.108	6.175
Instance *b*			
CC (M€)	29.254	31.568	55.012
CO (M€/y)	1.201	1.128	1.909
DO (mg/L)	5.800	5.849	5.939
Instance *c*			
CC (M€)	37.157	37.808	56.851
CO (M€/y)	1.607	1.550	1.998
DO (mg/L)	5.861	5.860	5.923

Next, we selected four possible combinations of weights (Table 5.3). Combination 1 attaches the same importance (33.3/100) to the three objectives. The other combinations give clearly more importance to one of the objectives (60/100) and divide the remaining weight equally between the other two objectives (20/100 each).

Table 5.3 - Combination of weights

Weight combination	Minimize capital cost	Minimize operating cost	Maximize dissolved oxygen
1	0.33(3)	0.33(3)	0.33(3)
2	0.60	0.20	0.20
3	0.20	0.60	0.20
4	0.20	0.20	0.60

Finally, we solved the model using the extreme values determined earlier for the three instances and the four combinations of weights. Again, this was performed using 10 seeds. The SAA parameters used in each instance were the same as those employed before in the evaluation of the extreme values. The evolution of the solution value (V) during the SAA process is shown in Figure 5.2, for instance *a*, combination 1 (similar evolutions were observed for the other instances and combinations). In the beginning of the process, V varies broadly between poor and fair solutions. As the algorithm proceeds, better solutions are found while the acceptance of poor solutions decreases, which leads to a more regular contour. When the algorithm arrives near the end, the evolution of V is given by a horizontal line, since the best value of V was reached.

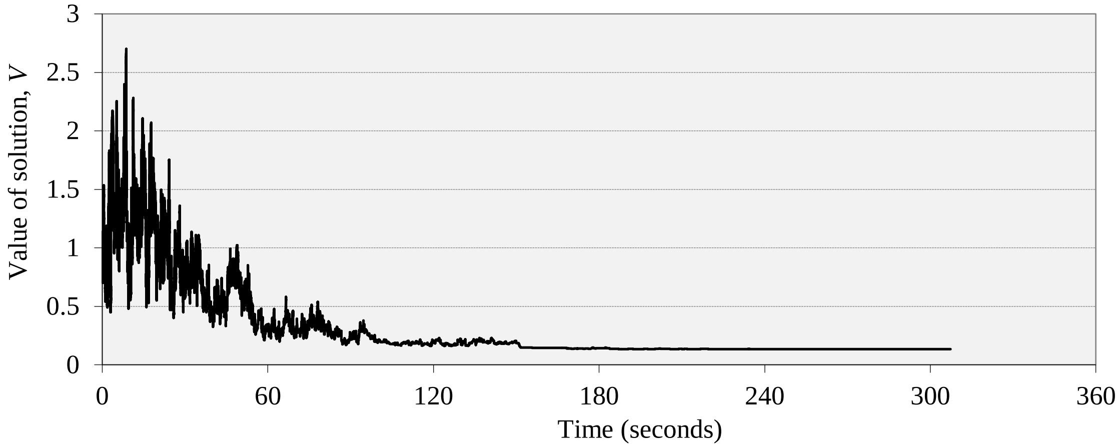


Figure 5.2 - Evolution of solution value during the SAA process

5.7. Multi-objective results

The results obtained for the three instances and the four weight combinations are presented in Table 5.4. This table contains the values obtained for the objective variables prior and after normalization, as well as the solution value. The normalized values for the objective variables are between 0% and 100% (which corresponds, respectively, to the best and worst extreme values of the variable). As expected, the best values of the objective variables were always obtained for the combination where the variables were given the highest weight.

Table 5.4 - Summary of results for instances a, b and c

	Weight Combination			
Variable	1	2	3	4
Instance *a*				
CC (M€)	26.078	23.670	23.790	26.896
CO (M€/y)	0.777	0.744	0.739	0.792
DO (mg/L)	6.170	6.125	6.125	6.174
CC'	19.75%	3.03%	3.86%	25.43%
CO'	14.50%	3.59%	1.96%	19.63%
DO'	6.60%	57.49%	57.49%	1.23%
V	0.136	0.140	0.134	0.098
Instance *b*				
CC (M€)	33.265	33.236	33.290	34.956
CO (M€/y)	1.185	1.186	1.184	1.211
DO (mg/L)	5.925	5.925	5.925	5.938
CC'	15.57%	15.46%	15.67%	22.13%
CO'	7.31%	7.43%	7.23%	10.71%
DO'	10.29%	10.29%	10.29%	0.61%
V	0.111	0.128	0.095	0.069
Instance *c*				
CC (M€)	40.052	40.052	40.402	40.482
CO (M€/y)	1.576	1.576	1.573	1.590
DO (mg/L)	5.921	5.921	5.921	5.922
CC'	14.70%	14.70%	16.48%	16.88%
CO'	5.84%	5.84%	5.01%	8.84%
DO'	2.70%	2.70%	2.70%	0.47%
V	0.077	0.105	0.068	0.054

The analysis of results indicates that there is a large trade-off between *CC* and *DO*, and also between *CO* and *DO* (the best solutions for *CC* and *CO* are the worst for *DO* and vice versa). In contrast, the trade-off between *CC* and *CO* is very small (but there is a trade-off since their best values never occurred simultaneously). The lowest solution values were always obtained for weight combination 4, i.e. when more weight was given to *DO*. This indicates that it is easier to find solutions where, at the same time, *DO* is near the optimum and the other objective variables have good-quality values.

In Figure 5.3 and Table 5.5, we present the results obtained for instance *a* using different weight combinations. The analysis of results shows how solutions adapt when more weight is given to each objective. With regard to the maximization of *DO*, it is possible to see that when more weight is attached to this objective, more money is spent in the treatment plants. In the top panels of Figure 5.3, w_{DO} = 0%, i.e. there is no concern with water quality. In the bottom left panel, corresponding to w_{DO} = 33%, the solution changes through siting a larger treatment plant in the first node, which allows the increase of *DO* (water quality) in the river. However, since w_{CC} = w_{CO} = 33%, the solution still takes cost minimization issues into account. The bottom right panel shows a solution where there is no concern with costs, since it corresponds to the maximization of *DO*, i.e. w_{DO} = 100%. This solution looks quite strange because of the unusual configuration and large length of the sewer networks. The reason for this is the fact that the only concern is with the wastewater flows to be discharged in the treatment plants.

The solutions shown also vary according to the weight given to *CC* and *CO*. When comparing the solution with the highest w_{CC} and the solution with the highest w_{CO}, the difference is with regard to the number of pump stations and the characteristics of the sewers. The cost of pump stations has more impact upon the operating costs, because of energy costs. As a result of this, when w_{CO} = 100% the number of pump stations is lower, with only one pump station, which leads to lower operating costs. When w_{CO} decreases, the number of pump stations increases. For w_{CO} = 33% there are four pump stations, whereas for w_{CO} = 0% and w_{CC} = 100% the number of pump stations increases to six. In contrast, for this combination of weights, the sewer length and average diameter is lower, because these are the characteristics with stronger implications upon capital costs. As referred to before, when w_{DO} = 100% the only concern is with the water quality in the river, which leads to the highest capital and operating costs.

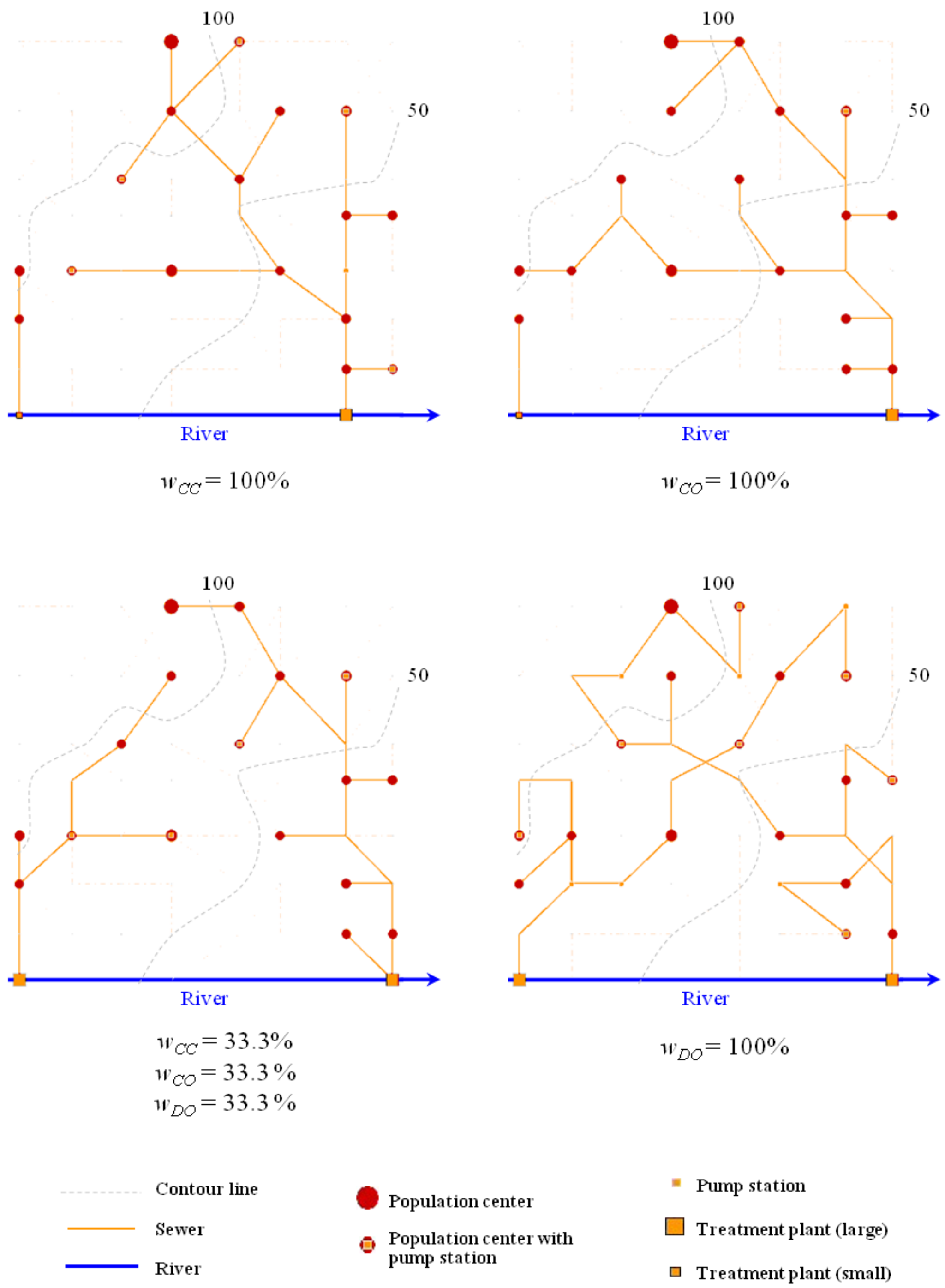


Figure 5.3 - System configurations obtained for instance *a* using different combinations of weights

Table 5.5 - Results obtained for instance *a* using different combinations of weights

Weights		w_{CC} = 100% w_{CO} = 0% w_{DO} = 0%	w_{CC} = 33,3% w_{CO} = 33,3% w_{DO} = 33,3%	w_{CC} = 0 % w_{CO} = 100% w_{DO} = 0%	w_{CC} = 0% w_{CO} = 0% w_{DO} = 100%
Number of Pump Stations		6	4	1	13
Sewer Lenght (km)		115.3	117.3	119.8	185.4
Sewer Average Diameter (mm)		428.9	455.9	446.0	470.7
Treatment Plant	CC (M€)	8.31	10.10	8.27	10.26
	CO (M€/y)	0.49	0.51	0.48	0.51

5.8. Conclusion

During the next few years, many wastewater systems will have to be built in many parts of the world if the objectives defined by the United Nations and other organizations are to be met. These systems will be more efficient both from the economic and the environmental standpoint if they are planned at a regional scale.

In this chapter, we presented a multi-objective model for regional wastewater systems planning where economic and environmental objectives are explicitly taken into account. The model is dealt with through the weighting method and solved through an SAA. The weighting method requires decision-makers to express their preferences either *a priori* or sequentially as they acquire a deeper understanding of the planning problem they are faced with. The type of results that can be obtained with the model was exemplified for three test instances designed to replicate real-world situations.

We believe that the model can already be useful for practical purposes in its current form. However, it can be improved with regard to some aspects. In particular, we think that the model should be enhanced to deal with uncertainty issues. Indeed, variables like population (thus, wastewater production) and river flow, which may have an important impact on infrastructure costs and water quality, cannot be estimated without error when designing a wastewater system to operate within a time span of, say, 20 years (usually more). Another aspect to improve regards the inclusion of environmental objectives other than DO (e.g. nitrogen and phosphorous). This is the kind of issue that our research in this field will address in the near future.

Chapter 6

Robust optimization approach to regional wastewater system planning

6.1. Introduction

The key importance of water for contemporary societies was recently reaffirmed by the United Nations in the Millennium Development Goals (UN 2005). The target of halving the number of people lacking sustainable access to safe drinking water and basic sanitation by 2015 mainly refers to problems faced by less-developed countries, but developed countries also have serious problems related with water quality (WWAP 2009). To attenuate these problems, appropriate wastewater systems have to be built or rebuilt in many places.

Wastewater system planning problems – as well as other infrastructure system planning problems – have typically been addressed through deterministic optimization approaches. However, such problems often involve significant demographic, economic, technological, and environmental uncertainties. Decision processes which do not properly consider these uncertainties may lead to substantially suboptimal solutions.

Uncertainty is a basic structural feature of planning, and the best way to deal with it, is to accept it, to structure it and understand it, and make it part of the decision making reasoning (Kouvelis and Yu 1997). A common strategy used to handle uncertainty in a structured way is scenario planning, wherein uncertainty is represented with a set of possible states of the world called scenarios (Rockafellar and Wets 1991). In the past, there was a plausible reason to justify the adoption of deterministic optimization approaches – the large computation burden involved in the consideration of uncertainty. But this reason is no longer valid. Indeed, processing power has been doubling approximately every two years (Moore's Law), and it is now usually possible to take uncertainty explicitly into account in infrastructure system planning in general, and wastewater system planning in particular. This will lead to more robust solutions to these systems – that is solutions that will perform well under all possible scenarios but are not necessarily optimal in any of them.

The theory and methodology that have been developed to handle optimization problems under uncertainty are described in a review by Sahinidis (2004), mostly relating to problems with multi-stage characteristics. Some widely used approaches that make use of scenario planning to deal with problems with uncertain parameters are: the stochastic optimization (SO) approach; the minimax approaches; and the robust optimization (RO) approach.

The SO approach recognizes the multiple outcomes that may be realized in the future, and associates probabilities with them (Mulvey and Ruszczynski 1995). It leads to decisions that optimize the expected value of an objective function according to the probability distribution function associated with the future scenarios.

The minimax approaches make use of robustness measures to find solutions that perform well in all scenarios while hedging against the worst possible scenario (Snyder 2006). These approaches do not require the association of probabilities with the scenarios. The robustness measures used more commonly are minimax cost and minimax regret. A minimax cost/regret solution is a solution for which the maximum cost/regret over all scenarios is minimized. The regret is the deviation between the value of a solution adopted in an uncertain context and the value of the solution that would have been adopted if there was no uncertainty.

The RO approach involves the use of probabilities for the future scenarios and incorporates the principles of the SO and minimax approaches through mean and variability measures, and allows for possible infeasibilities in the solution for some scenarios. This approach, which was introduced in a prominent article by Mulvey et al. (1995), thus embraces two robustness concepts: solution robustness and model robustness. Solution robustness relates to optimality, that is, whether the solution is "close" to optimal for any scenario. Model robustness relates to feasibility, that is, whether the solution is "almost" feasible for any scenario. Since solution robustness and model robustness are usually conflicting goals, they are represented with weighted terms, which provide a way to evaluate the tradeoffs between them as in a multi-objective approach.

The RO approach has gained a strong position in the optimization under uncertainty area, and has been used by some researchers on water-related problems. For instance, Watkins and McKinney (1997) applied this type of approach to water transfer and groundwater quality management problems. Kawachi and Maeda (2000) applied an RO approach to water quality management in an interconnected stream network, considering uncertainties in dissolved oxygen (DO) and biochemical oxygen demand (BOD) concentrations. More recently, the same type of approach was used by Ricciardi et al. (2007) on a groundwater flow problem and by Afonso and Cunha (2007) on the design of biological reactors and secondary settling tanks in wastewater treatment plants. With respect to water distribution systems, an RO approach was applied by Rosenberg and Lund (2009) to address shortage forecasts in a municipal water distribution system and by Cunha and Sousa (2010) to a problem involving uncertainty in the response capacity of infrastructure under extreme events.

In this chapter, we present three optimization models upon which a RO approach to regional wastewater system planning can be based. The system is to be designed for a region comprising several population centers (the wastewater sources). The wastewater generated in these centers must be collected and treated, in order to be discharged into a river. The infrastructure to build consists of sewer networks, treatment plants, and possible pump stations. The decisions to be made address two main issues: the setup and operation costs of infrastructure; and the water quality parameters to be met in the river where the (treated) wastewater is discharged. The source of uncertainty considered is the flow of the river. The solution for the wastewater system that satisfies the water quality parameters in the river largely depends on the river flow, as the environmental impact of wastewater discharges is higher when the flow is lower. Because of this, and because wastewater systems are often very costly and difficult to reverse, it is important that they are planned through a robust approach.

The chapter is organized as follows. In the next section we introduce the three optimization models upon which the RO approach to wastewater system planning can be based. Then, we describe the solution method used for solving the models. In the subsequent two sections, we describe the case study we used for testing the models, and present and compare the results obtained through their application. In the final section, we make some concluding remarks and point out directions for future research.

6.2. Optimization Models

Regional wastewater system planning has typically been addressed through deterministic optimization models with a cost-minimization objective. An example of such models is available in Sousa et al. (2002), the first article issued from our research in this area. An improved version of the initial model is described in Chapter 3. In Chapter 5 this model was extended to a multi-objective framework where cost and water quality objectives are coped with simultaneously. These models aim at determining an optimal solution for the layout of the sewer networks, and for the location, type, and size of treatment plants and possible pump stations to include in the system. The treatment plants are assumed to provide a given level of wastewater treatment. The objective function is subjected to constraints which ensure that the sewer network will be designed according to hydraulic laws and regulations. When the water quality objectives are not included in the objective function, constraints to ensure that the discharges from each treatment plant will not create environmental damage are considered. Water quality in the river is assessed according to parameters such as DO, BOD, nitrogen, and phosphorus concentration.

In this section, we extend our previous research in this field to uncertainty issues. Specifically, we propose three optimization models upon which a robust approach to regional wastewater system planning can be based, corresponding to three different ways of capturing uncertainty. To keep the models relatively simple we consider here that river flow is the only source of uncertainty and that water quality is only assessed in terms of DO concentration. The optimization models are designated as ROM 1, ROM 2, and ROM 3. Below we provide the constraints (common to the three models) and the objective-functions of the models.

6.2.1. Constraints

Using the sets, decision variables, and parameters presented in Table 6.1, the constraints of the optimization models can be formulated as follows:

6.2.1.1. Continuity Constrains

$$\sum_{j \in \boldsymbol{N_S} \cup \boldsymbol{N_I}} Q_{ji} - \sum_{j \in \boldsymbol{N}} Q_{ij} = -QR_i, \ \ i \in \boldsymbol{N_S} \tag{6.1}$$

$$\sum_{j \in \boldsymbol{N_S} \cup \boldsymbol{N_I}} Q_{jl} - \sum_{j \in \boldsymbol{N}} Q_{lj} = 0, \ \ l \in \boldsymbol{N_I} \tag{6.2}$$

$$\sum_{j \in \boldsymbol{N_S} \cup \boldsymbol{N_I}} Q_{jk} = QT_k, \ \ k \in \boldsymbol{N_T} \tag{6.3}$$

$$\sum_{i \in \boldsymbol{N_S}} QR_i = \sum_{k \in \boldsymbol{N_T}} QT_k \tag{6.4}$$

Constraints (6.1), (6.2), and (6.3) are the continuity equations for three types of network nodes: population centers, possible intermediate nodes, and possible treatment plants.

Constraints (6.4) ensure that all the wastewater generated by the population centers in the region will be treated at some treatment plant.

Table 6.1 – Notation of the constraints

Sets	
$\boldsymbol{N_S}$	set of population centers
$\boldsymbol{N_I}$	set of possible intermediate nodes (i.e., nodes that may be necessary to allow the appropriate representation of topography and/or the early regrouping of sewers)
$\boldsymbol{N_T}$	set of possible treatment plants and related river reaches
$\boldsymbol{N}$	set of nodes (population centers plus possible intermediate nodes plus possible treatment plants)
$\boldsymbol{T}$	set of treatment plant types
$\boldsymbol{S}$	set of scenarios
Decision Variables	
x_{ij}	binary variable that is equal to one if there is a sewer to carry wastewater from node i to node j, and is equal to zero otherwise
y_{ij}	binary variable that is equal to one if there exists a pump station for elevating wastewater from node i to node j, and is equal to zero otherwise
z_{kp}	binary variable that is equal to one if there is a treatment plant of type p at node k, and is equal to zero otherwise
Q_{ij}	flow carried from node i to node j
QT_k	amount of wastewater conveyed to a treatment plant located at node k
E_{ij}	difference of hydraulic heads between node i and node j
Parameters	
QR_i	amount of wastewater produced at node i
$Qmin_{ij}$	minimum flow allowed in the sewer linking node i to node j
$Qmax_{ij}$	maximum flow allowed in the sewer linking node i to node j
$QTmax_{kp}$	maximum amount of wastewater that may be treated at node k with a treatment plant of type p
$Q_{R,s}$	flow in the river for scenario s
$DO_{k,s}$	lowest DO concentration in river reach k for scenario s
$DO_{R,s}$	lowest DO concentration in the whole river for scenario s
C	discounted cost of the wastewater system
L_{ij}	length of the sewer linking node i to node j

6.2.1.2. Capacity Constraints

$$\sum_{p \in \boldsymbol{T}} z_{kp} \leq 1, \quad k \in \boldsymbol{N_T} \tag{6.5}$$

$$Q\,min_{ij}\; x_{ij} \leq Q_{ij} \leq Q\,max_{ij}\; x_{ij}\,, \quad i \in \boldsymbol{N_S} \cup \boldsymbol{N_I}\,, j \in \boldsymbol{N} \tag{6.6}$$

$$QT_k \leq \sum_{p \in \boldsymbol{T}} QT\,max_{kp}\; z_{kp}\,, \quad k \in \boldsymbol{N_T} \tag{6.7}$$

Constraints (6.5) guarantee that there will be at most one treatment plant, of a specific type, in each treatment node. Constraints (6.6) ensure that the flow carried by sewers will be within given minimum and maximum values. These values depend on the diameter and slope of sewers, and on flow velocity requirements. The hydraulic calculations needed to determine the diameter and slope of sewers can be performed using the well-known Manning equation. Constraints (6.7) ensure that the wastewater sent to any treatment plant will not exceed given maximum values. These values depend on the quality standards defined for the receiving water bodies and vary with the type of treatment plant.

6.2.1.3. Water Quality Constraints

$$DO_{k,s} = DO(\,QT_k\,, Q_{R,s}\,), \quad k \in \boldsymbol{N_T}\,, s \in \boldsymbol{S} \tag{6.8}$$

$$DO_{R,s} = \min_{k \in \boldsymbol{N_T}} DO_{k,s}\,, \quad s \in \boldsymbol{S} \tag{6.9}$$

Constraints (6.8) express the lowest DO concentration for a river reach, which depends on the treated wastewater discharged in the reach and all upstream reaches, and on the river flow (and other characteristics of the river). Constraints (6.9) specify the value for the lowest DO concentration in the whole river, which is the smallest of the lowest DO values for all river reaches.

6.2.1.4. Cost Constraints

$$C = \sum_{i \in \boldsymbol{N_S} \cup \boldsymbol{N_I}} \sum_{j \in \boldsymbol{N}} C_{ij}\left(Q_{ij}, L_{ij}, E_{ij}, x_{ij}, y_{ij}\right) + \sum_{k \in \boldsymbol{N_T}} \sum_{p \in \boldsymbol{T}} C_{kp}\left(QT_k, z_{kp}\right) \tag{6.10}$$

Constraints (6.10) specify the value for the discounted cost of setting up and operating the sewer network, pump stations and wastewater treatment plants. This cost depends on wastewater flows, on the length of the sewers, on the difference of hydraulic heads between the extremities of sewers, and on the amount of wastewater treated in each treatment plant.

6.2.1.5. Domain Constrains

$$x_{ij}, y_{ij} \in \{0,1\}, \quad i \in \boldsymbol{N_S} \cup \boldsymbol{N_I}, j \in \boldsymbol{N} \tag{6.11}$$

$$z_{kp} \in \{0,1\}, \quad k \in \boldsymbol{N_T}, p \in \boldsymbol{T} \tag{6.12}$$

$$Q_{ij}, E_{ij} \geq 0, \quad i \in \boldsymbol{N_S} \cup \boldsymbol{N_I}, j \in \boldsymbol{N} \tag{6.13}$$

$$QT_k \geq 0, \quad k \in \boldsymbol{N_T} \tag{6.14}$$

Constraints (6.11) to (6.14) specify the domain of the decision variables.

6.2.2. Objective Functions

6.2.2.1. ROM1

The objective function of the first optimization model is inspired by the model published in Laguna (1998) for the capacity expansion of telecommunications systems with demand uncertainty. The model includes a term for the minimization of the cost of the solution to be implemented and a penalty function for possible infeasibilities (that might occur when the solution is implemented).

The formulation of the objective function is as follows:

$$\text{Min } C+\theta\times\left[\sum_{s\in \boldsymbol{S}}\left(p_s\times\sum_{k\in \boldsymbol{N_T}}R_k\times max\left\{0; DO_{k,s}^{max}-DO_{k,s}\right\}^2\right)\right] \tag{6.15}$$

where C is the cost of the solution to be implemented; θ is a penalty coefficient applicable to the violation of water quality parameters; p_s is the probability of scenario s; R_k is the length of reach k; $DO_{k,s}^{max}$ is the lowest DO concentration in river reach k for scenario s when the lowest DO concentration in the whole river is maximized; $DO_{k,s}$ is the lowest DO concentration in river reach k for scenario s in the solution to be implemented.

The aim of this model is to find solutions that are close to the minimum cost while avoiding that the DO concentration in each river reach is “much” lower than the maximum that can be obtained, regardless of which scenario occurs. The first term of the objective function (6.15) represents the discounted cost of setting up and operating the sewer network, wastewater treatment plants, and pump stations. The second term is a quadratic penalty for the performance of the DO in the different river reaches. This term represents the feasibility of the water quality parameter by means of a regret for the DO, penalizing in each scenario the river reaches where $DO_{k,s}$ is lower than the respective $DO_{k,s}^{max}$.

6.2.2.2. ROM2

The objective function of the second optimization model is inspired by the scenario optimization model proposed in Dembo (1991). This model is applicable to portfolio immunization problems and was reintroduced by Mulvey et al. (1995) as scenario immunization (SI). In this type of model, the objective function is composed of a solution robustness term for the optimality of solutions and a model robustness term for penalizing possible solution infeasibilities in some scenarios.

The formulation of the objective function is as follows:

$$\text{Min} \sum_{s \in S} p_s \left[\left(C - C_s^{ref} \right)^2 + \beta \times max \left\{ 0, \left(DO_{R,s}^{ref} - DO_{R,s} \right)^2 \right\} \right] \tag{6.16}$$

where p_s is the probability of scenario s; C is the cost of the solution to be implemented; C_s^{ref} is the minimum discounted cost of the system when a lowest DO concentration in the whole river larger than $DO_{R,s}^{ref}$ is required for scenario s; β is a penalty coefficient applicable to the violation of water quality parameters; $DO_{R,s}^{ref}$ is the reference value for the desirable lowest DO concentration in the whole river for the scenario s; and $DO_{R,s}$ is the lowest DO concentration in the whole river for the scenario s in the solution to be implemented.

The aim of this model is to find solutions that are close to reference values in terms of cost and DO concentration in the whole river, regardless of which scenario occurs. The objective function (6.16) consists of a weighted sum of two terms. The first term corresponds to a regret function for the discounted cost of the system, that is, the difference between the discounted cost of the solution to be implemented and the C_s^{ref} of each scenario. Notice that the cost of the solution to be implemented is the same for all scenarios. The second term corresponds to a quadratic penalty for the performance of DO in the whole river. This term represents the feasibility of the water quality parameter by means of a regret for the lowest DO, penalizing the scenarios that have a $DO_{R,s}$ smaller than the $DO_{R,s}^{ref}$. Both terms in this model therefore represent regret with respect to reference values. Since the C_s^{ref} are obtained through the $DO_{R,s}^{ref}$, the terms might be slightly correlated. Unlike the SI model, ROM2 requires the use of a penalty coefficient β since the values for the two terms of the objective function are not of the same order of magnitude. This penalty coefficient also allows the assessment of the tradeoff between solution robustness and model robustness.

6.2.2.3. ROM3

The objective function of the third optimization model is inspired by a model introduced in Malcolm and Zenios (1994) and applied in Mulvey et al. (1995) to a power capacity expansion problem under uncertain power demand. This model balances the tradeoffs between solution robustness, represented by a mean-variance formulation, and model robustness, represented by a penalty term. The mean-variance formulation reduces the chance of solutions that are particularly weak in some scenarios being selected, while the penalty term promotes the feasibility of the solution.

The formulation of the objective function is as follows:

$$\text{Max} \sum_{s\in S} p_s DO_{R,s} - \lambda \sum_{s\in S} p_s \left(DO_{R,s} - \sum_{s\in S} p_s DO_{R,s} \right)^2 - \omega\left[C - C_{min}\right] \tag{6.17}$$

where p_s is the probability of scenario s; $DO_{R,s}$ is the lowest DO concentration in the whole river for the scenario s in the solution to be implemented; λ and ω are weights expressing the importance of water quality variance and wastewater system cost, respectively; C is the cost of the solution to be implemented; and C_{min} is the minimum discounted cost of the system.

The aim of this model is to find solutions that maximize the expected value of the lowest DO concentration in the whole river while minimizing the variability of the lowest DO across scenarios and taking into account the economic feasibility of solutions through a penalty on cost. The first term represents the expected DO_R for the solution, the second accounts for the variability of the DO_R by means of its variance, and the third penalizes the difference between the cost of the solution to be implemented and the minimum cost of the system. Weights λ and ω can be modified to allow the analysis of tradeoffs between the expected DO_R, the variance of DO_R, and the cost of the solution. Larger values of λ should result in solutions with less variability under the different scenarios that might occur. Lower cost solutions should be expected for larger values of ω.

6.3. Solution Method

For solving the complex discrete non-linear optimization models described in the preceding sections, we implemented a simulated annealing (SA) algorithm enhanced with a local improvement (LI) procedure (Dowsland, 1993; Kirkpatrick et al., 1983). Previous work has shown the SA algorithm to be extremely efficient at finding optimal or near-optimal solutions when applied to regional wastewater system planning (Chapter 4).

The SA algorithm starts with any initial feasible solution (the initial incumbent solution). Then a candidate solution is selected at random in the neighborhood of the incumbent solution. The candidate solutions better than the incumbent solution are always accepted (becoming the incumbent solution), whereas candidate solutions worse than the incumbent solution may or may not be accepted. This is important because it helps the algorithm to avoid getting stuck in local optima. The transition between solutions is regulated by a parameter called temperature, according to a cooling schedule. The probability of accepting a worse solution decreases with the difference in value between the candidate and the incumbent solution and with the current temperature. The algorithm proceeds while the temperature is lowered in a controlled manner until the value of solutions ceases to increase.

The LI procedure starts with the best solution identified through the SA algorithm as the incumbent solution. Then it moves into the best solution within all possible solutions in the neighborhood of the incumbent solution. By doing this in successive iterations until no better solutions can be found, the LI procedure is expected to improve on the solution obtained by the SA algorithm (Chapter 4).

For each candidate solution, a hydraulic model is used to design sewers, treatment plants, and possible pump stations complying with all relevant regulations. In addition, a water quality model is used to estimate the effects of wastewater discharges in the river. This model evaluates the water quality parameters of the river taking into consideration atmospheric reaeration, photosynthesis, respiration, sediment oxygen demand, carbonaceous organic matter oxidation, and nitrification (Chapter 3).

6.4. Case Study

The robust optimization models presented in the previous section were tested on a case study involving a randomly-generated rectangular region extending approximately 197 km along a river, with a breadth of 71km and a maximum height of 557 meters (see Figures 6.1 and 6.2). A total of 66 nodes were considered in the region, including 31 population centers (the wastewater sources) and 11 possible locations for wastewater treatment plants. The total population of the region is approximately 884,000. The daily wastewater generation rate per inhabitant was assumed to be 200 liters.

The flow in the river was assumed to follow a normal distribution with a mean of 12 m^3/s and a standard deviation of 3 m^3/s. After discretization, 18 scenarios were considered with flows between 3 and 21 m^3/s (Table 6.2). The range of flow values (mean ± 3 standard deviations) covers 99.73% of occurrence probabilities. Each scenario corresponds to an interval of variation of 1 m^3/s. The design flow considered for each scenario, $Q_{R,s}$, is the worst-case flow for that scenario (that is, the minimum flow).

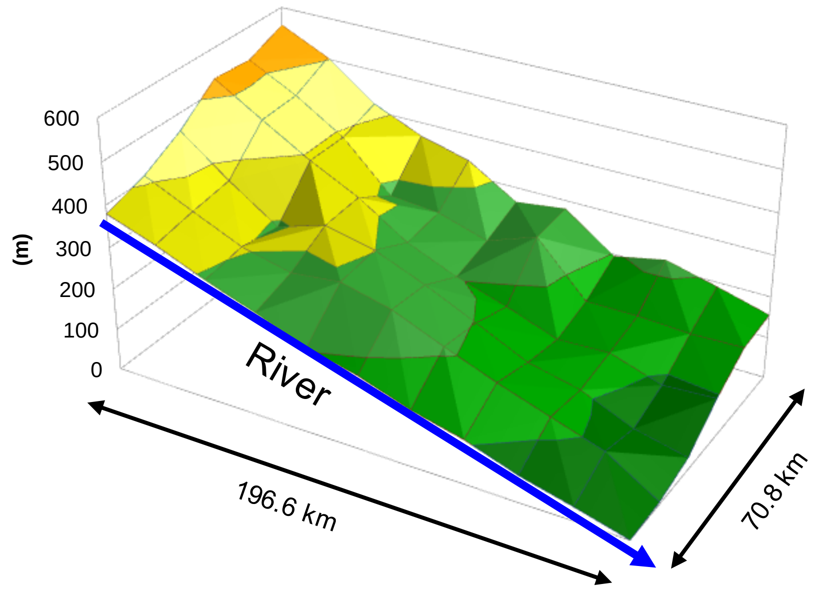


Figure 6.1 - Topography of the case study region

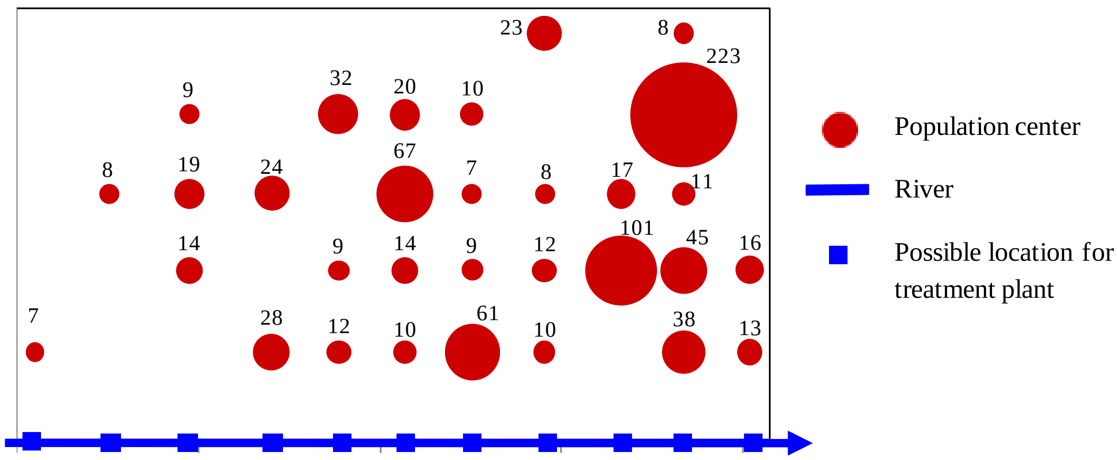


Figure 6.2 - Spatial distribution of population and possible location for treatment plants (values close to population centers indicate population in thousands)

Table 6.2 - Scenario-dependent parameters

Scenario	Q_R (m^3/s)	p_s (%)	DO_R^{max} (mg/l)	DO_R^{ref} (mg/l)	C^{ref} (M€)
1	3	0.25	5.16	4.90	358.98
2	4	0.60	5.76	5.47	350.97
3	5	1.29	6.17	5.86	339.32
4	6	2.50	6.49	6.17	326.76
5	7	4.34	6.74	6.40	314.61
6	8	6.74	6.93	6.59	305.63
7	9	9.38	7.08	6.73	296.72
8	10	11.69	7.22	6.86	285.32
9	11	13.06	7.32	6.96	277.71
10	12	13.06	7.42	7.05	269.83
11	13	11.69	7.51	7.13	259.95
12	14	9.38	7.58	7.20	251.75
13	15	6.74	7.64	7.26	244.71
14	16	4.34	7.70	7.32	238.54
15	17	2.50	7.75	7.37	236.41
16	18	1.29	7.80	7.41	233.73
17	19	0.60	7.85	7.45	232.33
18	20	0.25	7.88	7.49	231.42

Other data involved in the case study for the three RO models relate to the cost and DO parameters for each scenario under consideration. To calculate these parameters for each scenario *s*, the deterministic wastewater system planning model presented in Chapter 3 was solved either with the objective of minimizing costs or, changing the objective-function, with the objective of maximizing water quality.

In the case of ROM1, the parameter is DO_k^{max}, and corresponds to the lowest DO in each river reach when the wastewater system is designed to maximize the lowest DO in the whole river. Table 6.3 shows the values of DO_k^{max} for some scenarios chosen to represent the variability of river flow (note that, starting in Table 6.3, scenarios are identified with the respective Q_R). These values, as well as the value for DO_R^{max} (the maximum lowest DO concentration in the whole river) were obtained from the deterministic model with a DO_R maximization objective (Table 6.2).

Table 6.3 - Values of DO_k when the wastewater system is designed to maximize the DO_R

River Reach	DO_k^{max}(mg/l) Scenario – Q_R (m^3/s) 3	9	14	20
1	5.48	7.38	7.86	8.14
2	5.17	7.09	7.60	7.92
3	5.20	7.08	7.58	7.89
4	5.16	7.16	7.58	7.89
5	5.17	7.10	7.62	7.90
6	5.43	7.11	7.58	7.89
7	5.26	7.12	7.59	7.91
8	5.27	7.18	7.68	7.99
9	5.51	7.35	7.81	8.09
10	5.86	7.52	7.94	8.18
11	5.16	7.08	7.58	7.88

As regards ROM2, the parameters are DO_R^{ref} and C^{ref}. The DO_R^{ref} is a reference value for the water quality to be guaranteed in the whole river. For the case study, it was set to 95% of the DO_R^{max}. The C^{ref} is the minimum cost for a system that meets the desired water quality. Its value is obtained by solving the deterministic model with the cost minimization objective, when DO_R is constrained to be greater than DO_R^{ref}. The values of these parameters for the various scenarios are presented in Table 6.2. For instance, for a scenario with Q_R = 12 m^3/s, the DO_R^{max} is 7.42 mg/l, thus the DO_R^{ref} is 7.05 mg/l. For this scenario the value obtained for C^{ref} is 269.83 M€. As expected, C^{ref} values are higher for lower values of the river flow, because when the flow in the river is low the discharge of the treated wastewater has to be spread out more along the river to mitigate environmental impacts, and so sewer networks have to be longer and more pump stations have to be included in the wastewater system.

In the case of ROM3, the parameter is C_{min}, and corresponds to the minimum cost solution for the case study. It is obtained through the deterministic model with a cost minimization objective and no water quality constraints, and its value is 231.42 M€.

6.5. Model Results

6.5.1. Results for ROM1

ROM1 was applied to the case study with three values for the penalty coefficient θ: 0, 10^3, and 10^6. The results obtained for the optimal DO_k are shown in Table 6.4 with respect to some scenarios. Solving ROM1 with $\theta = 0$ is the same as solving the deterministic wastewater system planning model with a cost minimization objective and no water quality constraints, thus we achieved the same cost as before (231.42 M€). With respect to the values of DO in the river reaches, although the larger values of DO decrease as the penalty coefficient increases, the lowest DO in the river reaches increases. For instance, for the scenario with Q_R = 3 m^3/s, the DO_R is 3.24 mg/l for θ = 0, and 4.87 mg/l for $\theta = 10^6$. But the cost increases as θ increases – it is 267.16 M€ for $\theta = 10^3$, and 433.15 M€ for $\theta = 10^6$. The time taken to solve this model ranged from 4 hours for $\theta = 0$ to 8 hours for $\theta = 10^6$.

Table 6.4 - Values of optimal DO_k for the different θ of ROM1

River Reach	DO_k (mg/l)											
	$\Theta = 0$				$\Theta = 10^3$				$\Theta = 10^6$			
	Scenario – Q_R (m^3/s)											
	3	9	14	20	3	9	14	20	3	9	14	20
1	8.61	8.71	8.74	8.76	8.60	8.71	8.74	8.76	**5.24**	7.43	7.92	8.19
2	8.59	8.65	8.67	8.68	8.00	8.46	8.54	8.60	**4.87**	7.15	7.68	7.98
3	8.62	8.65	8.66	8.67	8.00	8.45	8.53	8.57	**4.89**	7.15	7.66	7.95
4	7.88	8.44	8.53	8.58	**5.10**	7.33	7.81	8.07	5.17	**7.12**	7.60	7.89
5	7.85	8.43	8.53	8.58	**4.77**	7.16	7.69	7.99	5.28	7.14	**7.61**	**7.89**
6	7.88	8.44	8.54	8.59	**4.78**	7.16	7.68	7.98	**5.28**	**7.10**	**7.57**	**7.86**
7	5.63	7.60	8.01	8.23	**5.04**	7.21	7.70	7.99	5.31	**7.11**	**7.58**	**7.87**
8	5.40	7.47	7.92	8.17	5.57	7.37	7.80	8.05	5.61	7.24	**7.67**	**7.93**
9	**5.44**	7.47	7.92	8.17	6.18	7.58	7.93	8.15	6.09	7.45	**7.80**	**8.03**
10	**5.72**	7.54	7.95	8.19	6.63	7.76	8.05	8.23	6.49	7.63	**7.93**	**8.12**
11	**3.24**	**6.20**	**7.01**	**7.50**	**4.13**	**6.59**	**7.26**	**7.67**	5.22	**7.06**	**7.56**	**7.88**

6.5.2. Results for ROM2

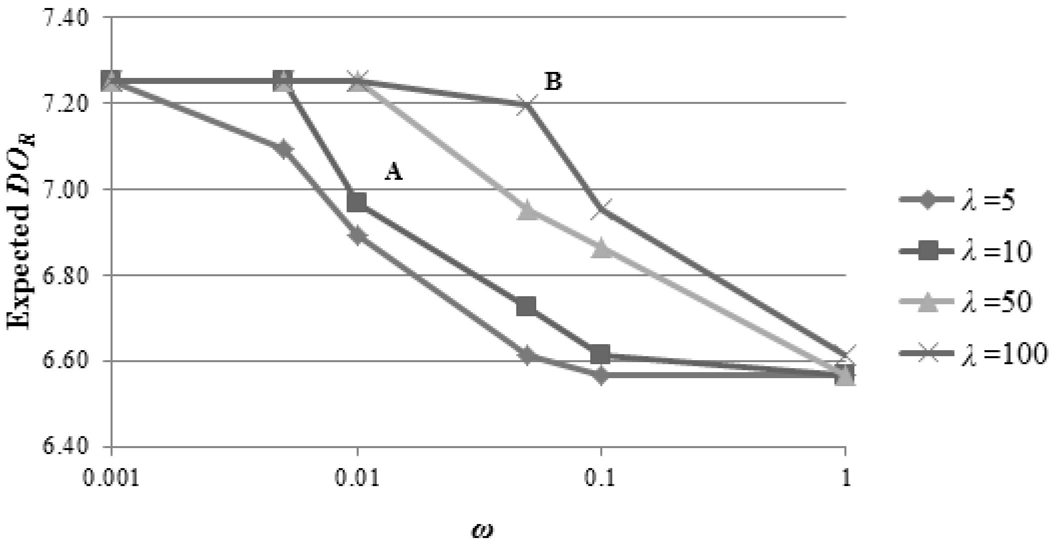
ROM2 was also solved for three values of the penalty coefficient β: 0, 10^3, and 10^6. As the value of this coefficient increases, solutions are expected to comply better with DO requirements. The results obtained for the DO_R of each scenario are shown in Table 6.5 together with the results obtained for ROM1 and ROM3, to allow comparison. It is clear that, as the penalty coefficient increases, the lowest DO in all the scenarios increase. For instance, for the scenario with Q_R = 3 m^3/s, the DO_R is 3.57 mg/l for β = 0, and 4.59 mg/l for $\beta = 10^6$. But the cost of the solution increases as β becomes larger – it is 275.07 M€ for β = 0, 275.10 M€ for $\beta = 10^3$, and 311.16 M€ for $\beta = 10^6$. The computation time taken to solve the model was between 3 hours for β = 0 and 9 hours for $\beta = 10^6$.

Table 6.5 - Values of DO_R for the RO models

	DO_R (mg/l)							
Scenario	ROM1			ROM2			ROM3	
Q_R (m^3/s)	$\theta = 0$	$\theta = 10^3$	$\theta = 10^6$	$\beta = 0$	$\beta = 10^3$	$\beta = 10^6$	*Solution A*	*Solution B*
3	**3.24**	**4.13**	**4.87**	**3.57**	**4.20**	**4.59**	**4.45**	5.05
4	**4.13**	**4.87**	5.62	**4.40**	**4.93**	**5.25**	**5.13**	5.64
5	**4.77**	**5.41**	6.13	**5.00**	**5.46**	**5.72**	**5.62**	6.06
6	**5.26**	**5.81**	6.48	**5.45**	**5.85**	**6.08**	**5.99**	6.37
7	**5.64**	**6.13**	6.72	**5.81**	**6.17**	**6.37**	**6.29**	6.62
8	**5.95**	**6.38**	6.91	**6.10**	**6.42**	6.59	**6.52**	6.82
9	**6.20**	**6.59**	7.06	**6.33**	**6.62**	6.77	**6.71**	6.98
10	**6.42**	**6.77**	7.19	**6.53**	**6.79**	6.93	6.87	7.12
11	**6.60**	**6.92**	7.31	**6.70**	**6.94**	7.06	7.01	7.24
12	**6.76**	**7.05**	7.41	**6.85**	7.07	7.18	7.13	7.34
13	**6.89**	7.16	7.49	**6.98**	7.18	7.28	7.24	7.43
14	**7.01**	7.26	7.56	**7.09**	7.28	7.37	7.33	7.50
15	**7.12**	7.35	7.63	**7.19**	7.36	7.45	7.41	7.57
16	**7.21**	7.43	7.69	**7.28**	7.44	7.52	7.48	7.64
17	**7.30**	7.50	7.74	**7.36**	7.51	7.58	7.55	7.69
18	**7.37**	7.56	7.78	7.43	7.57	7.64	7.61	7.74
19	**7.44**	7.62	7.82	7.50	7.63	7.69	7.66	7.79
20	7.50	7.67	7.86	7.56	7.68	7.74	7.71	7.83

6.5.3. Results for ROM3

ROM3 was applied to several combinations of weights λ and ω. Weight λ reflects the importance ascribed to the variance of DO_R, while weight ω corresponds to a penalty term representing cost regret. Figure 6.3 gives the results for this model, illustrating the relationship between the expected DO_R, the cost, and the weights ω and λ. It shows that when ω increases not only the cost decreases but also the values for the expected DO_R decreases. It also shows that higher values of λ results in higher expected DO_R, but higher costs as well.



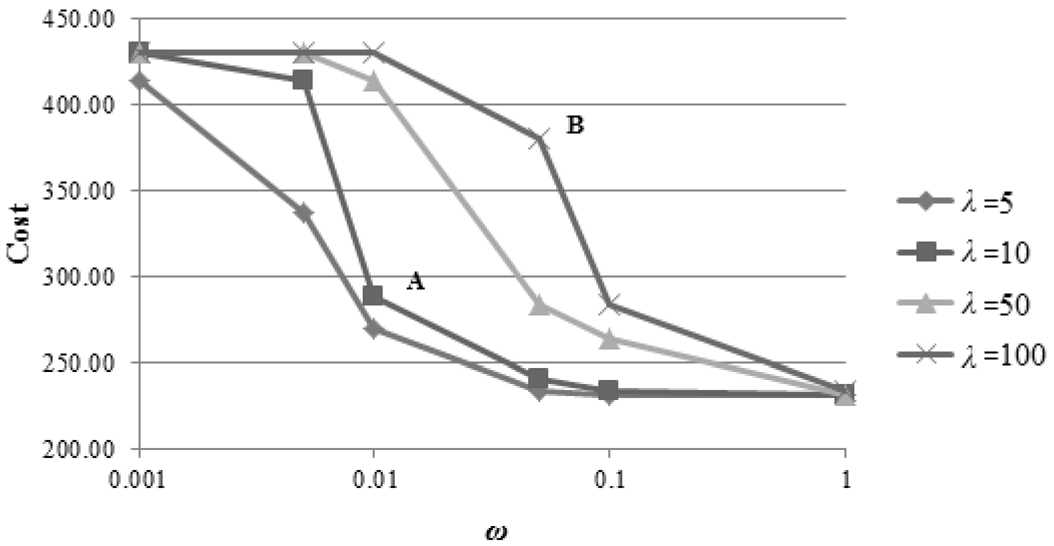


Figure 6.3 - Impact of weights (λ and ω) on expected DO_R and cost

ROM3 provides a large set of solutions, from which the decision-maker can choose in accordance to his goals. For instance, appropriate solutions could be like the ones represented in Figure 6.3. *Solution A*, with $\lambda = 10$ and $\omega = 0.01$, has the highest expected DO_R (6.97 mg/l) for a cost lower than 300.00 M€. *Solution B,* with $\lambda = 100$ and $\omega = 0.05$, has the lowest cost (380.28 M€) with an expected DO_R at least equal to 7.20 mg/l.

The cost of *Solution B* is larger than *Solution A* but, in addition to a larger expected DO_R, *Solution B* has a larger DO_R for all the possible scenarios (Table 6.5). The computation time taken to solve the model was about 3 hours for *Solution A* and 4.5 hours for *Solution B*.

6.5.4. Comparison of results with deterministic version of the model

The results for the three RO models (ROM1, ROM2 and ROM3) can be compared in terms of cost and DO with some of the results obtained through the determinist version of the regional wastewater system planning model.

Table 6.5 shows the results for the DO_R in each scenario for the different penalties θ and β of ROM1 and ROM2 respectively, as well as for the selected *Solution A* and *Solution B* of ROM3. The results in bold in this table are those where the DO_R is smaller than the DO_R^{ref} shown in Table 6.2.

In the case of ROM1, the figures in bold in Table 6.4 are those that were penalized in the objective function, since they are smaller than the values given in Table 6.3. As referred before, the solution for ROM1 with $\theta = 0$ is the same as solving the deterministic wastewater system planning model with a cost minimization objective. For $\theta = 10^6$, despite more reaches being penalized, the level of the lowest DO is close to the best possible, including for extreme flow events (lower Q_R). In addition, as shown in Table 6.5, for $\theta = 10^6$ only the scenario with lower flow ($Q_R = 3$ m^3/s) has a value of DO_R (4.87 mg/l) that does not achieve the respective DO_R^{ref} (4.90 mg/l). But for $\theta = 10^6$, the cost (433.15 M€) is larger than the C^{ref} obtained, even for the scenarios associated with the most expensive costs. Regarding $\theta = 10^3$, the cost (267.16 M€) is similar to the C^{ref} obtained for the scenarios with larger probabilities.

As regards ROM2, full compliance is achieved if DO_R^{ref} is attained for all scenarios. But the results show that even for values of β of 10^6 this did not happen. For the lower values of β, the costs (275.07 M€ for $\beta = 0$ and 275.10 M€ for $\beta = 10^3$) are similar to the C^{ref} obtained for the scenarios with larger probabilities. In the case of $\beta = 10^6$, the cost (311.16 M€) is lower than the C^{ref} obtained for the scenario with $Q_R = 7$ m^3/s (314.61 M€), while having a DO_R in that scenario (6.37 mg/l) close to the respective DO_R^{ref} (6.40 mg/l).

In the case of ROM3, *Solution B* has a cost (380.28 M€) larger than the C^{ref} for all the scenarios. However, *Solution B* is the only solution where the DO_R is larger than the DO_R^{ref} for all scenarios (Table 6.5). For *Solution A*, the cost (288.1 M€) is lower than the C^{ref} obtained for the scenario with $Q_R = 9$ m^3/s (296.72 M€), while having a DO_R in that scenario (6.71 mg/l) close to the respective DO_R^{ref} (6.73 mg/l).

Assuming that for this case study would be used a typical deterministic approach considering a value for the Q_R such as 9 m^3/s, the cost of the solution obtained would be 296.72 M€ and the DO_R would be 6.73 mg/l (Table 6.2). This deterministic solution for $Q_R = 9$ m^3/s has lower cost than the ROM1 with $\theta = 10^6$, ROM2 with $\beta = 10^6$, and *Solution B* of ROM3. When comparing to all the remaining solutions of the RO models this deterministic solution has a larger cost, but apparently also a larger DO_R, as its value is larger in the scenario with $Q_R = 9$ m^3/s (Table 6.5). However, to compare this solution in terms of robustness, the behavior of the solution for all the remaining scenarios need to be evaluated. When performing this evaluation in terms of DO_R, its values are between 3.83 mg/l for the scenario with Q_R = 3 m^3/s and 7.71 mg/l for the scenario with Q_R = 20 m^3/s. Therefore, for the lower flows, the DO_R obtained by this deterministic solution would be indeed much lower than the obtained by ROM1 with $\theta = 10^3$, ROM2 with $\beta = 10^3$, and *Solution A* of ROM3 (Table 6.5). So, the solutions obtained by the three RO models are robust in the way that they are better suited to perform well under all scenarios, while they are still close to the best in each scenario. For larger values of the penalty coefficients, the solutions become more robust, and their implementation will lessen the vulnerability of the wastewater system.

6.5.5. Comparison of results between the three RO models

The results for the three RO models (ROM1, ROM2 and ROM3) are now compared in terms of cost, DO_R, treated wastewater discharges and configuration.

Table 6.6 shows the results for the cost and expected DO_R for the different penalties θ and β of ROM1 and ROM2 respectively, as well as for the selected *Solution A* and *Solution B* of ROM3.

Table 6.6 - Values of expected DO_R and cost for the RO models

Model	ROM1			ROM2			ROM3	
	$\theta = 0$	$\theta = 10^3$	$\theta = 10^6$	$\beta = 0$	$\beta = 10^3$	$\beta = 10^6$	*Solution A*	*Solution B*
Expected DO_R (mg/l)	6.55	6.87	7.26	6.65	6.89	7.02	6.97	7.20
C (M€)	231.42	267.16	433.15	275.07	275.10	311.16	288.11	380.28

With respect to the costs, ROM1 easily achieved the lowest cost solution, since for low values of θ the model becomes similar to the deterministic cost minimization model, while in ROM2, for low values of β the model seeks a cost similar to C^{ref}. The costs of the selected solutions of ROM3 are within the range of figures obtained for the other models. In terms of the expected DO_R of the solutions and the DO_R for each scenario, the largest value of θ in ROM1 provided the maximum value of expected DO_R, but at a very high cost. In ROM2 the DO_R moves towards the reference lowest DO instead of the maximum lowest DO, as in ROM1. This results in a smaller expected DO_R for a high β, but also in a smaller cost. *Solution B* of ROM3 is the only solution where the DO_R is larger than the DO_R^{ref} for all scenarios. This was achieved regardless of there being an expected DO_R worse than that obtained by ROM1 and a cost more than 10 per cent smaller.

The values of the optimal discharges at the wastewater treatment plants (QT_k) for the different penalties θ and β of ROM1 and ROM2 respectively, as well as for the selected *Solution A* and *Solution B* of ROM3, are shown in Table 6.7. As might be expected, when larger weights are assigned to the terms related with DO_R discharges tend to be less concentrated and become more evenly distributed along the river. Solutions with the discharges more spread out along the river do not necessarily comprise a larger number of wastewater treatment plants. A solution leading to a small DO_R, ROM1 for $\theta = 0$, involves five wastewater treatment plants, while a solution leading to a large DO_R, *Solution B* of ROM3, involves four wastewater treatment plants.

Table 6.7 - Discharges at the treatment plants for the RO models

River Reach	QT_k (m^3/s)							
	ROM1			ROM2			ROM3	
	$\theta = 0$	$\theta = 10^3$	$\theta = 10^6$	$\beta = 0$	$\beta = 10^3$	$\beta = 10^6$	*Solution A*	*Solution B*
1	17	17	886	0	17	187	17	785
2	0	114	0	17	114	0	0	0
3	0	0	0	0	0	569	729	0
4	178	825	173	178	864	0	0	64
5	0	0	24	0	0	28	0	0
6	0	0	252	720	0	444	444	529
7	640	0	0	0	0	0	0	0
8	23	0	0	0	0	0	0	0
9	0	0	0	23	0	0	0	0
10	0	0	0	0	0	0	0	0
11	1188	1090	711	1108	1051	818	856	668

The optimal configurations of the wastewater system for the different RO models are displayed in Figure 6.4. In the solutions obtained when larger weights are assigned to the terms related with DO_R the sewer networks are longer, to spread the wastewater along the river. Because of this, and because several pump stations are needed due to the topography of the region, the cost of these solutions is higher. This is evident for ROM1 with $\theta = 10^6$, ROM2 with $\beta = 10^6$, and ROM 3 - *Solution B*. For ROM1 with $\theta = 0$, that is, when no weight is assigned to the term related with DO_R , the optimal configuration with the lowest cost is obtained, as the wastewater generated in larger population centers is sent to close treatment plants. In contrast, for ROM2 with $\beta = 0$, the configuration of the solution has some sewers apparently located in sub-optimal positions. This is because this solution only aims for a cost similar to the expected value of C^{ref}. Only for larger values of β does the DO_R of the solution also heads towards DO_R^{ref}, which results in a configuration more similar to what could be expected. The solutions for ROM1 with $\theta = 10^3$ and ROM2 with $\beta = 10^3$ are similar, which is corroborated by the similar discharges, and by the figures for the costs and the expected DO_R.

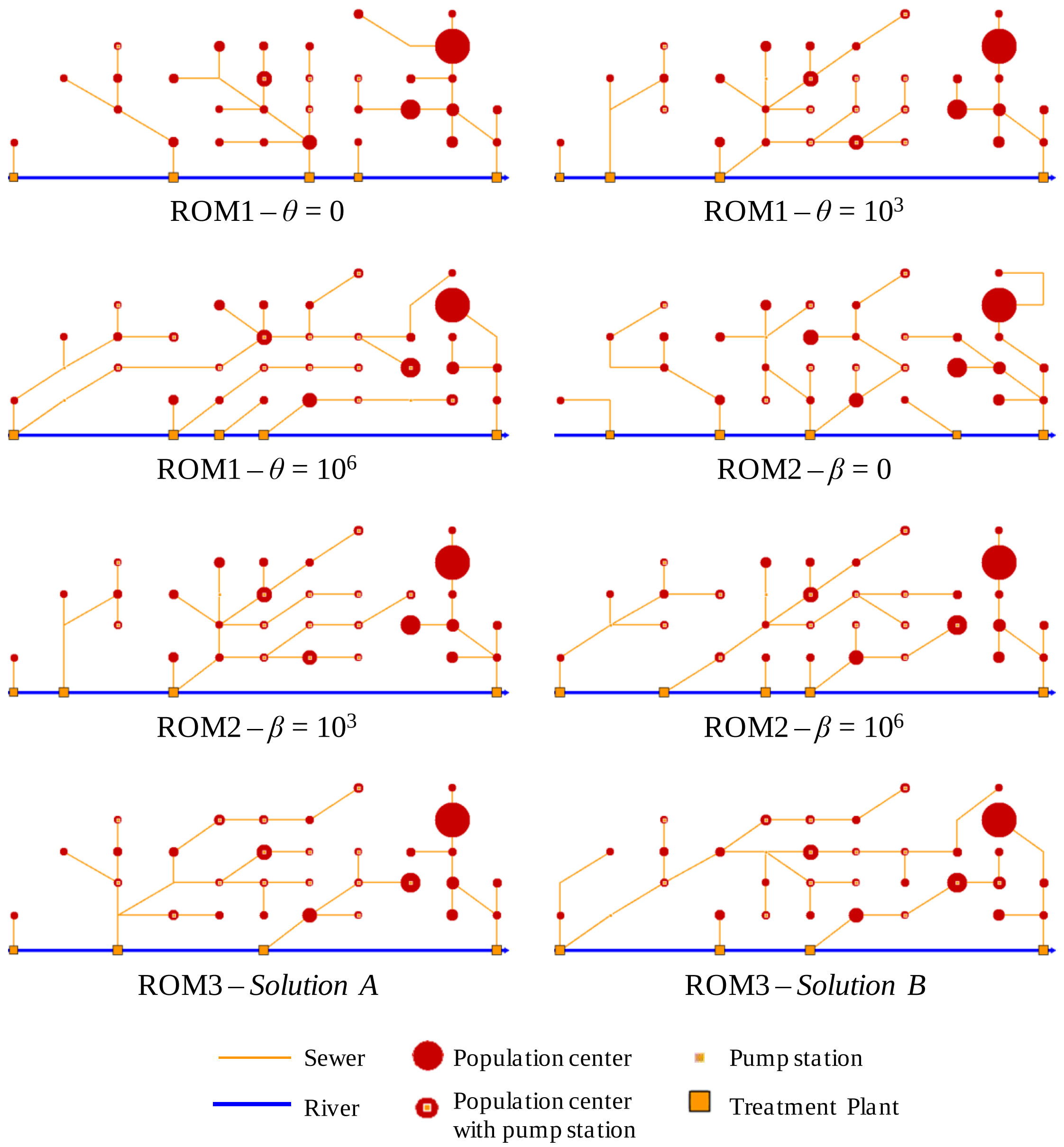


Figure 6.4 - Optimal configuration of the wastewater system

6.6. Conclusion

In this chapter we have presented three optimization models upon which to base a robust approach to regional wastewater system planning. The models assume that uncertainty can be represented through a set of scenarios with known probabilities. The purpose is to find a wastewater system configuration that, regardless of which scenario occurs, is feasible and close to optimal when cost and water quality objectives are considered. The models correspond to three different ways of capturing uncertainty. For solving the models we adapted a simulated annealing algorithm enhanced with a local improvement procedure that we previously developed to deal with deterministic planning problems. The models were tested on a case study with results that indicate its potential usefulness in real-world applications. A comparison of the results obtained for each of the three models was presented to assess their respective strengths and weaknesses. This comparison was made between the models and also with some of the results obtained through the determinist version of the regional wastewater system planning model.

The work described in this chapter explores an important direction of research, as infrastructure failure or ill-functioning attributable to the lack of consideration of uncertainty issues in the planning stage is less and less tolerated in contemporary societies. It is also an important direction owing to the technical challenges involved in the shift from a deterministic to a robust approach. Robust approaches are indeed much more complex conceptually and, as a result of this, the models upon which they are based are much more difficult to solve and their results are much more difficult to interpret. The case study included in the chapter clearly confirms these assertions. But it also clearly shows that the use of a robust approach can provide wastewater system administrators with a much better insight into the decisions to make, and that today this can be achieved within quite reasonable computational effort (given the large planning horizons that characterize infrastructure planning).

The robust approach presented in this chapter can be further improved through the consideration of uncertainty in other variables – such as the amount of wastewater generated in the population centers in the region where the system is to be built, which depends on the demographic and economic evolution of the region – and the cost of wastewater systems components. The implications of uncertainty in these variables upon the configuration of regional wastewater systems are complex, and raise issues that we did not deal with. These are issues where we intend to focus our research efforts in the near future.

Chapter 7

Regional wastewater system design under population dynamics uncertainty

7.1. Introduction

World demographics have been facing several changes due to human population dynamics for a long time. Populations can change through three processes: fertility, mortality and migration. Fertility and mortality are responsible for the continuing population growth that is happening in the world today, originating in developing countries. Migration may result from the regional or international relocation of a population or the movement of people between rural and urban areas. Because of urbanization, the urban population has risen from about 10% of the world population at the beginning of the 20^{th} century to more than 50% today (UN 2010). Suburbanization is also gaining some relevance in some developed countries. The migration processes associated with population growth result in particularly intense population dynamics.

Rising populations have more needs for a civilized life and this affects essential resources. The water bodies not only suffer water stress, they are also contaminated by the large amounts of pollution that are generated, largely relating to domestic household sewage. Wastewater systems are crucial to guaranteeing the quality of the receiving water bodies, which is vital for a sustainable development. The investment needed for these systems is often very large but it can be largely recouped through the benefits obtained (WBCSD 2008). These systems should therefore be planned efficiently to take into account the costs involved and the quality achieved by the receiving water bodies. Even though these systems are often planned at local level, planning at regional level can result in better solutions, in both economic and environmental terms (Chapter 3). However, such planning is affected by the uncertainty over the amounts of wastewater involved, that is, the population that could occur in an as yet unknown future.

The projections of future populations are an essential component of many planning studies but they are inherently inaccurate due to the processes related to population dynamics. A usual procedure is to perform different projections, and select one as the basis for planning, by accessing the impact of data perturbations. But not introducing uncertainty into the planning of an infrastructure system can result in a solution that is either over-conservative or over-optimistic, leading to inefficient or ineffective decision-making. A proactive approach will, by design, ensure solutions less sensitive to data perturbations (Mulvey et al. 1995). A robust approach will help to achieve that end for planning problems such as those relating to regional wastewater systems by embodying all the possible outcomes that might occur in the future into the planning. This enables a search for a robust solution, that is, a solution that will perform well under all possible outcomes but is not necessarily optimal in any of them.

The goal of this chapter is to present a robust approach for regional wastewater system planning under population dynamics uncertainty. The source of uncertainty considered stems from the future population projection for the region being studied. The infrastructure to drain and treat the wastewater generated in the region includes the following facilities: wastewater treatment plants (WWTP) to process the wastewater before it is discharged into rivers; sewer networks connecting the population centers with the WWTP; and pump stations to lift wastewater if it is unfeasible or uneconomic to drain it by gravity. The best way to search for an optimal configuration in terms of cost and water quality in the river where the wastewater is discharged is to use an optimization model (Chapter 3). An optimization model for regional wastewater system planning under uncertainty is described here. Its aim is to achieve robust solutions less sensitive to the uncertainties in the problem. The proposed model minimizes the expected regret for the cost of the system, and also considers the disregard of worst-case scenarios through the use of the alpha-reliable concept. To illustrate the results that can be obtained, the model is applied to a case study based on a real world situation from a European Union NUTS III (Nomenclature of Units for Territorial Statistics) region in Portugal.

The chapter is organized as follows. The different aspects of the problem are presented in section 7.2. The optimization model and its solution method are explained in section 7.3. Section 7.4 sets out the case study, and the results are presented and discussed in section 7.5. The last section draws some conclusions.

7.2. Problem presentation

7.2.1. Regional wastewater system planning

Wastewater systems drain the wastewater generated by human populations and date back about seven thousand years. Apart from the Roman Empire, their planning and design were generally limited, until modern wastewater systems were developed, less than two centuries ago. It is also only recently that the crucial importance of wastewater treatment has been recognized and considering in planning. When both the economic and environmental concerns are taken into account, planning at regional level can provide better solutions. The search for the best regional wastewater system should rely on optimization-based approaches to allow full exploration of possible planning solutions. The literature contains several optimization models for the regional planning of wastewater systems, as presented in the surveys by Melo and Câmara (1994) and Whitlatch (1997) on the first optimization models applied. More complex models have been proposed in which varied techniques are applied to solve them, such as heuristic methods. The models presented by Wang and Jamieson (2002) and Sousa et al. (2002) are examples of the application of modern heuristics to regional wastewater system planning problems. Genetic algorithms have also been developed recently to solve models for the regional waste load allocation problem (Cho et al. 2004, Yandamuri et al. 2006, Aras et al. 2007). In a location model formulation of a regional wastewater system planning problem Leitão et al. (2005) make use of a solution method based on Geographic Information System (GIS) and greedy algorithms. An evolutionary global optimization method was applied by Álvarez-Vasquez et al. (2008) to a regional wastewater system planning of a coastal area. Other commercial solvers were applied to the grey optimization model defined by Chang and Hernandez (2008) for the planning of a wastewater system expansion under uncertainty, and to the integrated water system planning model with wastewater recycle purposed by Lim et al. (2010).

The optimization model recently presented by Chapter 3 is a prominent approach for the regional wastewater system planning that employs a heuristic method based on a simulated annealing (SA) algorithm This approach consists of a deterministic formulation designed to find an optimal solution for the layout of the sewer networks, and for the location, type, and size of the pump stations and treatment plants to include in the system. Its objective function concerns the cost of the solution to be implemented, in terms of cost minimization, and is subjected to various constraints to ensure that the sewer network will be designed according to hydraulic laws and regulations. In Chapter 5 the objective function of the Chapter 3 deterministic model was extended to a multi-objective version to explicitly handle the presence of environmental goals in the objective function. Otherwise, constraints to ensure that the treated effluent discharged from each treatment plant would not damage the environment have been considered. Therefore, the system must ensure that the wastewater discharged from each treatment plant will not exceed a given maximum amount, consistent with the water quality standards set for the receiving water body.

Traditionally, the approaches reported in the regional wastewater system planning literature have been based on deterministic optimization models and fail to account for any uncertainty component. Robust approaches are required to deal with uncertainties inherent to the problem's variables such as the amounts of wastewater in the region being studied. These amounts are uncertain due to population dynamics, which makes it difficult to project the population that will occur in the time frame of the planned system.

7.2.2. Robust approach

A major strategy for dealing with optimization problems under uncertainty is through scenario planning. The uncertainties in the optimization model can be represented by a set of possible scenarios that provide possible courses of future events. Because of the complexity of regional wastewater systems, a solution for one worst case scenario might not be feasible in other scenarios. Equally, a solution for a hypothetical scenario that simultaneously included the maximum amounts of each wastewater source within all scenarios would be far oversized.

Scenario planning considers the different scenarios and aims to find a solution that will perform well in all scenarios (Rockafellar and Wets 1991). Robust approaches often employ stochastic formulations that make use of scenario planning to optimize the expected performance of the systems, according to the probability distribution function associated with the future scenarios. The performance can be accessed, for instance, in terms of the minimum cost of the system to be implemented. As with the optimization of the expected performance, an alternative approach optimizes the expected regret of the solution. Regret is the deviation between the payoff of a solution selected with limited information and the best payoff that could be obtained if all information was available at the time of the selection (Loomes and Sugden 1982).

To make some decision models more realistic and less conservative, Daskin et al. (1997) introduced the alpha-reliable concept, developing a framework for the problem of minimization of the maximum regret (minimax regret). It captures the risk aversion by restricting the scenario space through a specified reliability level called α. The minimax regret solution is only computed over an endogenously selected subset of scenarios, the reliability set, whose collective probability of occurrence is at least α. The traditional minimax regret problem is a particular example in which $\alpha = 1.0$.

7.2.3. Population projections

Population projections are needed for purposes such as planning studies, and can make use of different approaches. The review by Booth (2006) sets out three approaches: trend extrapolation, using historical patterns to predict the future; expectation methods, by means of subjective prospects; and explanation methods, through the use of structural models. Most approaches are based on component methods that combine projections of births, deaths, and migration to update a population. The cohort-component method is based on similar logic for individual age groups, which is useful in planning situations where demographic characteristics are needed. Other decomposition and disaggregation can also be applied. But the more complex approaches do not generally lead to more accurate forecasts of total population than can be achieved with simpler models (Smith 1997). This is mainly because there is some irreducible level of uncertainty about the future that no method can counter, however sophisticated it is. Keilman (2008) came to a similar conclusion that population forecasts are intrinsically uncertain after showing that demographic forecasts published by several statistical agencies are no more accurate than they were twenty-five years ago. Assuming that future errors can be drawn from the same distribution as past errors, it is possible to take advantage of ex post errors to improve future forecasts. Keyfitz

(1981) and Stoto (1983) pioneered the analysis of ex post errors to derive probability distributions of population size in current forecasts. The data on the distribution of past forecasting errors can therefore be used, for instance, to construct empirical confidence intervals for population forecasts (Smith and Sincich 1988, De Beer 2000).

Among the factors that influence the accuracy of the projection outcomes are the time frame and level of regional aggregation. Errors tend to cancel each other out over larger scales. The degree of uncertainty grows and projections became more inaccurate for smaller regions and long term horizons, resulting in values subject to considerable uncertainty (Smith et al. 2001). The growth rate and migration of a region's population depends on what occurs in the country as a whole. However, the internal variability of a demographic trend at regional scale is larger and more complex than at national scale, and fewer works dealing with small-area projections have been published (Wilson and Bell 2007). There are several factors that might generate significant internal migration within a region's population centers, even if this does not affect the total population of the region. To evaluate the accuracy of small-area population projections Murdock et al. (1991) proposed that growth patterns are inclined to be accentuated or muted by the population characteristics of an area, and thus presented relevant groups of characteristics. In small-area forecasts, Tayman et al. (1998) and Rayer et al. (2009) assumed that future errors will be drawn from the same distribution as past forecasting errors and constructed confidence intervals for sub-county and county areas.

7.3. Optimization model

This chapter addresses regional wastewater system planning through a robust approach to deal with the uncertainty in the amounts of wastewater generated that arises from the population projections in the region in study. An optimization model that seeks to determine robust solutions for the regional wastewater system is presented. The model extends the deterministic model described in Chapter 3 to a stochastic formulation, making use of scenario planning to find solutions that are expected to perform well under the set of possible future situations. The objective function consists of minimizing the expected regret of the solution. The regret associated with a scenario is given by the difference between the cost of the solution implemented and the best cost that can be obtained under that scenario. The environmental concern is integrated through constraints on the treatment plant's dimensions. To include risk-aversion, possible infeasibilities were considered by restricting scenario space through the alpha-reliable concept. The model will lead to robust solutions, which are near-optimal and feasible with a certain level of reliability.

The model formulation of the robust approach to the regional wastewater system planning is presented in the next sections. First, the general model is proposed, consisting of the expected regret minimization without including reliability measures. Then a variation of the model is presented, with the same objective of minimizing the expected regret but including the alpha-reliable concept (Daskin et al. 1997), thus enabling it to disregard some low probability scenarios that affect the value of the solution most negatively. The last variation of the model is also based on the alpha-reliable concept, but only in some facilities and in such a way that solutions will remain feasible for all scenarios. We also provide information on the method used to solve the model.

7.3.1. Minimization of the expected regret

The objective of the general model is to minimize the expected regret of the solution. The essential ingredients of the model are:

$$\text{minimize } W \tag{7.1}$$

subject to:

$$\sum_{j \in \boldsymbol{N_S} \cup \boldsymbol{N_I}} Q_{jis} - \sum_{j \in \boldsymbol{N}} Q_{ijs} = -QR_{is}, \quad i \in \boldsymbol{N_S}; s \in \boldsymbol{S} \tag{7.2}$$

$$\sum_{j \in \boldsymbol{N_S} \cup \boldsymbol{N_I}} Q_{jls} - \sum_{j \in \boldsymbol{N}} Q_{ljs} = 0, \quad l \in \boldsymbol{N_I}; s \in \boldsymbol{S} \tag{7.3}$$

$$\sum_{j \in \boldsymbol{N_S} \cup \boldsymbol{N_I}} Q_{jks} = QT_{ks}, \quad k \in \boldsymbol{N_T}; s \in \boldsymbol{S} \tag{7.4}$$

$$\sum_{i \in \boldsymbol{N_S}} QR_{is} = \sum_{k \in \boldsymbol{N_T}} QT_{ks}, \quad s \in \boldsymbol{S} \tag{7.5}$$

$$\sum_{p \in \boldsymbol{T}} z_{kp} \leq 1, \quad k \in \boldsymbol{N_T} \tag{7.6}$$

$$Q_{min_{ij}}\, x_{ij} \leq Q_{ijs} \leq Q_{max_{ij}}\, x_{ij}, \quad i \in \boldsymbol{N_S} \cup \boldsymbol{N_I}; j \in \boldsymbol{N}; s \in \boldsymbol{S} \tag{7.7}$$

$$QT_{ks} \leq \sum_{p \in \boldsymbol{T}} QT_{max_{kp}}\, z_{kp}, \quad k \in \boldsymbol{N_T}; s \in \boldsymbol{S} \tag{7.8}$$

$$R_S - \left(C_s - \hat{C}_s \right) = 0 \ , \qquad s \in \boldsymbol{S} \tag{7.9}$$

$$W - \sum_{s \in \boldsymbol{S}} p_s \, R_s = 0 \tag{7.10}$$

$$x_{ij}, y_{ij} \in \{0,1\}, \quad i \in \boldsymbol{N_S} \cup \boldsymbol{N_I} \, ; \, j \in \boldsymbol{N} \tag{7.11}$$

$$z_{kp} \in \{0,1\}, \ \ k \in \boldsymbol{N_T} \, ; \, p \in \boldsymbol{T} \tag{7.12}$$

$$Q_{ijs} \geq 0, \quad i \in \boldsymbol{N_S} \cup \boldsymbol{N_I} \, ; \, j \in \boldsymbol{N} \, ; s \in \boldsymbol{S} \tag{7.13}$$

$$QT_{ks} \geq 0, \ \ k \in \boldsymbol{N_T} \, ; s \in \boldsymbol{S} \tag{7.14}$$

where W is the expected regret of the solution to be implemented; $\boldsymbol{N_S}$ is a set of wastewater sources; $\boldsymbol{N_I}$ is a set of possible intermediate nodes (i.e. nodes that may be needed to allow the appropriate representation of topography and/or the early regrouping of sewers); $\boldsymbol{N_T}$ is a set of possible treatment plants and related river reaches; $\boldsymbol{N}$ is a set of nodes (wastewater sources plus possible intermediate nodes plus possible treatment plants); $\boldsymbol{T}$ is a set of treatment plant types; $\boldsymbol{S}$ is a set of scenarios; Q_{ijs} is the flow carried from node i to node j under scenario s; QR_{is} is the amount of wastewater produced at node i under scenario s; QT_{ks} is the amount of wastewater conveyed to a treatment plant located at node k under scenario s; $Q_{min_{ij}}$ and $Q_{max_{ij}}$ are the regular minimum and maximum flow allowed in the sewer linking node i to node j respectively; $QT_{max_{kp}}$ is the maximum amount of wastewater that may be treated at node k with a treatment plant of type p; R_s is the regret associated with scenario s; C_s is the cost of the solution to be implemented under scenario s; $\hat{C}_s$ is the minimum cost of the solution for the scenario s; p_s is the probability of scenario s; x_{ij} is the binary variable that takes the value one if there is a sewer to carry wastewater from node i to node j, and is zero otherwise; y_{ij} is a binary variable that takes the value one if there is a pump station for taking wastewater from node i to node j, and is zero otherwise; and z_{kp} is a binary variable that takes the value one if there is a treatment plant of type p at node k, and is zero otherwise.

The objective function (7.1) of this approach minimizes the expected regret. Constraints (7.2), (7.3), and (7.4) are the continuity equations for three types of network nodes: wastewater sources, possible intermediate nodes, and possible treatment plants. Constraints (7.5) ensure that all the wastewater generated in the region will be treated at one treatment plant or another. Constraints (7.6) guarantee that there will be at most one treatment plant, of a specific type, in each treatment node. Constraints (7.7) ensure that the flow carried by sewers will be within given minimum and maximum regular values. These values depend on the diameter and slope of sewers, and on flow velocity requirements. The hydraulic calculations needed to determine the diameter and slope of sewers are performed using the well-known Manning equation. Constraints (7.8) ensure that the wastewater sent to any treatment plant will not exceed given maximum values. These values depend on the quality standards defined for the receiving water bodies and vary with the type of treatment plant. Constraint (7.9) stipulates the regret associated with scenario s in terms of the global cost of the solution, as discussed previously. Constraints (7.10) define the expected regret of the solution to implement. Constraints (7.11) to (7.14) specify the domain of the decision variables.

This optimization model aims to find a solution that, according to the probability distribution function, has a cost near the best cost of each scenario, while it is completely feasible in any scenario that might occur, even the worst-case scenarios. Hence, the solutions obtained are expected to be completely reliable, since all the facilities of the wastewater system are designed to work in perfect conditions whatever scenario occurs.

7.3.2. Alpha-reliable expected regret

7.3.2.1. a-reliable

The model of expected regret minimization can be extended to some variations that embrace the alpha-reliable concept. The purpose of the first and main variation is to minimize the expected regret of the solution for a defined reliability of a wastewater system that might be infeasible for some scenarios.

For the formulation of this model, constraints (7.7), (7.8) and (7.10) from the model of expected regret minimization are replaced by the following:

$$Q_{min_{ij}}\, x_{ij} Z_s - M_{Q\,min} x_{ij}(Z_s - 1) \le Q_{ijs} \le Q_{max_{ij}}\, x_{ij} Z_s - M_{Q\,max} x_{ij}(Z_s - 1),$$
$$i \in \boldsymbol{N_S} \cup \boldsymbol{N_I};\ j \in \boldsymbol{N};\ s \in \boldsymbol{S} \qquad (7.15)$$

$$QT_{ks} \le \sum_{p \in \boldsymbol{T}} QT_{max_{kp}}\, z_{kp} Z_s - M_{QT}(Z_s - 1),\ \ k \in \boldsymbol{N_T};\ s \in \boldsymbol{S} \qquad (7.16)$$

$$W - \sum_{s \in \boldsymbol{S}} p_s\, R_s\, Z_s = 0 \qquad (7.17)$$

$$\sum_{s \in \boldsymbol{S}} p_s Z_s \geq \alpha \tag{7.18}$$

$$Z_s \in \{0,1\} \quad , \qquad s \in \boldsymbol{S} \tag{7.19}$$

where α is the reliability parameter; Z_s is a binary variable that takes the value one if scenario s is included in the set over which the minimization is taken, and is zero otherwise; W is the α-reliable regret of the solution to be implemented; M_{Qmin} is a very small constant; M_{Qmax} and M_{QT} are very large constants.

Constraints (7.15) ensure that, for the scenarios in the reliability set, that is, the subset of scenarios over which the regret is computed, the flow carried by sewers will be within given minimum and maximum regular values. M_{Qmin} and M_{Qmax} are constants that must be set small and large enough, respectively, so that the size of wastewater facilities will not be dependent on scenarios not included in the reliability set. Constraints (7.16) ensure that, for the scenarios in the reliability set, the wastewater sent to any treatment plant will not exceed given maximum values. M_{QT} is a constant that must be set large enough so that the maximum capacity of treatment plants will not be applied to scenarios not included in the reliability set. Constraint (7.17) defines the expected regret of the solution to implement, taking into account the decisions on which scenarios to include in the reliability set. The parameter α defines the minimum probability associated with the set of scenarios over which the regret is computed, and it is guaranteed by constraint (7.18). Constraint (7.19) is an integrality constraint.

In this approach, the model is aimed at finding solutions that are close to optimal and reliable for most of the scenarios. All the facilities of the solutions contained in the reliability set are feasible, while for the remaining (1-α) of the scenarios, some facilities might be undersized if such scenarios occur in the future. This optimization model endogenously disregards the (1-α) of the scenarios that most negatively influence the objective function, meaning that the solution will not be designed to accommodate some worst-case scenarios.

7.3.2.2. *a'-reliable*

The second variation of the model of expected regret minimization has the objective of minimizing the expected regret of the solution for all scenarios, considering a reliability set for the performance of some facilities of a wastewater system that must be feasible for all scenarios.

Normally, sewers are sized to work in perfect conditions, such as with a depth of flow no larger than half of the sewer diameter. This value relates to the $Q_{max_{ij}}$ and is usually defined in regulations to guarantee ventilation and prevent septicity in the sewer. When this value rises, the sewer is allowed to carry a larger flow but it will work under undesirable conditions. However, the solutions will still be feasible up to the maximum flow of $Q_{MAX_{ij}}$, which represents a depth of flow that is 0.94 times the diameter of the sewer.

For the formulation of this model, constraints (7.7) from the model of expected regret minimization are replaced by the following:

$$Q_{min_{ij}}\, x_{ij} \le Q_{ijs} \le Q_{max_{ij}}\, x_{ij} Z_s' - Q_{MAX_{ij}} x_{ij} \left(Z_s' - 1\right), \qquad i \in \boldsymbol{N_S} \cup N_I;\ j \in \boldsymbol{N};\ s \in \boldsymbol{S} \tag{7.20}$$

$$\sum_{s \in \boldsymbol{S}} p_s Z_s' \geq \alpha' \tag{7.21}$$

$$Z_s' \in \{0,1\} \quad , \qquad s \in \boldsymbol{S} \tag{7.22}$$

where α' is the reliability parameter for the sewer behavior; Z_s' is a binary variable that takes the value one if scenario s is included in reliability set, and is zero otherwise; and $Q_{MAX_{ij}}$ is the maximum feasible flow allowed in the sewer linking node i to node j.

Constraints (7.20) ensure that the flow carried by sewers will be larger than given minimum regular values for any scenario. For the scenarios in the reliability set the flow carried by sewers will be lower than given maximum regular values, and will never exceed maximum feasible values for scenarios not included in the reliability set. The parameter α' defines the minimum probability associated with the reliability set, and is guaranteed by constraint (7.21). Constraint (7.22) is an integrality constraint.

In this approach, the regret is computed for the entire set of scenarios as with the model of expected regret minimization. Thus, this model aims at finding solutions that are close to optimal and completely feasible in any scenario that might occur, even the worst-case scenarios. However, a reliability set is considered so that some facilities are allowed to work in inadequate conditions in some scenarios. This reliability set implies that each of these facilities, in this case sewers, is designed to work in regular conditions in at least α' of the scenarios. In the rest (1-α') of the scenarios some sewers might not work perfectly, but these sewers as well as the overall solution for the wastewater treatment system are still feasible.

7.3.3. Model solving

The above-described optimization model representing the problem shows nonlinear characteristics and discrete variables. Even for small-scale instances, models of this type can be extremely difficult to solve and should therefore be handled through heuristic algorithms. The SA algorithm was proposed by Kirkpatrick et al. (1983), since when much work has been done on SA and it has been applied in a wide range of contexts. A brief description of different modifications to the SA algorithm can be found in Eglese (1990). In this chapter, following the work carried out by the authors on regional wastewater system planning, an SA algorithm enhanced with a local improvement (LI) procedure is implemented (Chapter 4).

The basic idea of the algorithm involves several steps. In each step of the SA algorithm, a change of solution is produced, chosen at random in the neighborhood of the incumbent solution. For each candidate solution a hydraulic model is used to design sewers, possible pump stations, and treatment plants, complying with all relevant regulations, and then its cost is calculated. Neighborhood moves to a candidate solution better than the incumbent solution are always accepted. The SA algorithm attempts to avoid becoming trapped in a local optimum by sometimes accepting candidate solutions worse than the incumbent solution. The transition between solutions is regulated by a parameter called temperature, according to a cooling schedule. Initially, even very negative transitions will be accepted, but as the temperature falls, the acceptance of such transitions will become increasingly rare. The SA algorithm proceeds until the value of solutions ceases to increase, and then the LI procedure starts. The LI procedure searches all the solutions in the neighborhood of the incumbent solution and moves into the best solution if its value exceeds the value of the incumbent solution. By doing this in successive iterations, until no further improvement can be found, the LI procedure can be expected to improve on the solution obtained by the SA algorithm.

There are three important aspects in the implementation of the algorithm: definition of the initial incumbent solution; definition of the neighborhood of an incumbent solution; and definition of the cooling schedule of the SA algorithm. Since the SA is a random search algorithm, the best solution was selected from the run of a set of 20 different random seeds. For more information on the algorithm, see Chapter 4. The solution method also contemplates a complete enumeration method to evaluate all the possible combinations of the alpha-reliable set in the model.

7.4. Case study

The results that may be obtained by applying the approach presented in this chapter are illustrated with an academic example based on a region from Portugal, where the wastewater sources correspond to a set of small areas matching the communities of the region. The wastewater system to be planned for the region depends on the future amounts of wastewater related to the population of the wastewater sources. One of the most important issues addressed in planning studies like those for regional wastewater systems is the demand projection, that is, the population projection. Because it is a projection for the future, there is an uncertainty component. The solution for the regional wastewater system should be designed to accommodate a set of possible future populations that is originated by the uncertainty in the projection. In this case study the target year for the population projection is 2021.

The study reported in this chapter relies heavily on a geographic information system (GIS) for data handling and analysis of the results. Geographic data available for the study region includes boundaries of communities, population center locations, heights, census tracts and existing treatment plants' locations. The GIS was used to define the locations of intermediate nodes and compute the distances between them and wastewater sources, and to display the solution obtained on a map. Displaying model solutions on a map considerably facilitates the diagnosis of model errors and the interpretation of model results.

The case study is characterized in section 7.4.1 below. The projected population of this region is shown in section 7.4.2, allowing the generation of the different scenarios. The cost functions for the wastewater system are then briefly presented in section 7.4.3. Finally, section 7.4.4 presents the minimum cost solution figures for each of the scenarios, which are parameters required for the model described in this chapter.

7.4.1. Study area

The case study was based on a real world region, situated in Portugal. This area is called Baixo Mondego, according to the NUTS III division of Portugal in 2008. The respective area is 2,063 km^2, and the population at the census in 2001 was 340,309 inhabitants. Figure 7.1 shows the study area, divided into 8 municipalities which are subdivided into a total of 106 communities ("freguesias", the smallest administrative unit in Portugal).

The Baixo Mondego region is more or less cut in half by the major river of the region, the Mondego, which is the longest river contained exclusively in Portuguese territory. The study area has some similarity to the Mondego River Basin, downstream of the large dam of Aguieira which was constructed in 1979 to manage the flow of the river. The Mondego Basin has one of the main water resources exploitation operations in the country, for purposes such as energy production, flow control, irrigation, and water supply. Two areas can be considered, given the demarcation line of the river: South Baixo Mondego, corresponding to the left bank; North Baixo Mondego, corresponding to the right bank.

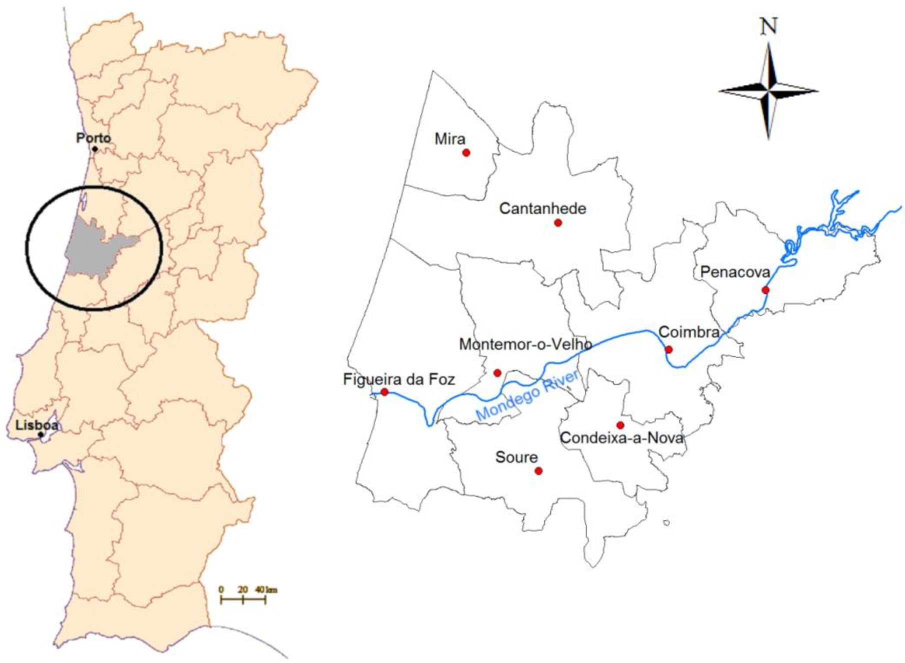


Figure 7.1 - Municipalities and major river in the Baixo Mondego region of Portugal

The study area is quite flat downstream of the capital city of the region, Coimbra, particularly along the banks where there is significant farming. The only exception is the mouth of the river near the second major city, Figueira da Foz. In the upstream areas the topography is rougher, reaching a maximum altitude of more than 500 m. We considered that the entire population and wastewater generation of each community is represented by a single node located in its geometric center. Figure 7.2 shows the geography of the case study region. This is represented by the spatial distribution of the communities and by the topography of the region, represented by the contour lines and the Mondego River.

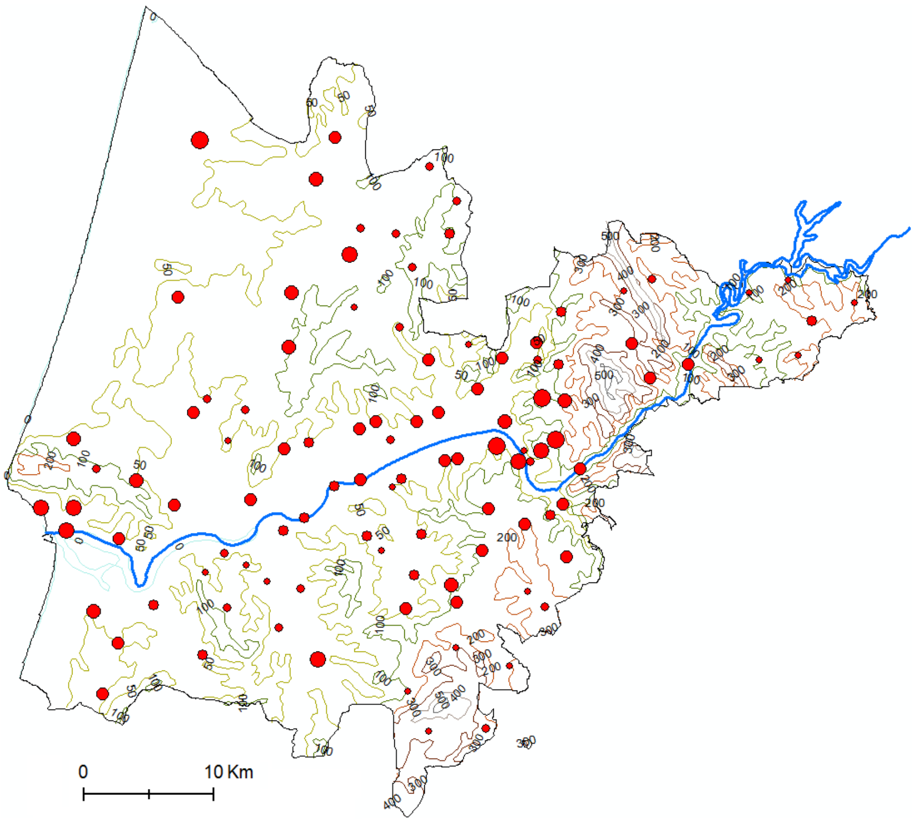


Figure 7.2 - Topography and spatial distribution of communities in the study area

The wastewater system selected for the case study refers only to the North Baixo Mondego area, consisting of 56 communities. Several possible links were defined between the wastewater sources nodes. The heights of these nodes were taken from the contour lines, and 21 intermediate nodes were defined to account for slope changes and possible intersection of sewers. The possible locations for WWTPs were based on the actual location of WWTPs at the moment, although the case study considers there are none, and they have an associated capital cost when selected for construction in the decision. The maximum coverage for these WWTPs is 150 thousand inhabitants, which is the same capacity as the largest WWTP currently operating in the region. Figure 7.3 shows the wastewater sources nodes, possible intermediate nodes and possible locations for the WWTP of the case study region, including all the 482 links possibilities between them.

The number of inhabitants in the communities, that is, the wastewater generation and respective drainage and treatment demand, are related to an as yet unknown horizon year and is thus the subject of some uncertainty. A population projection is required to estimate these figures, to be performed over the entire Baixo Mondego region.

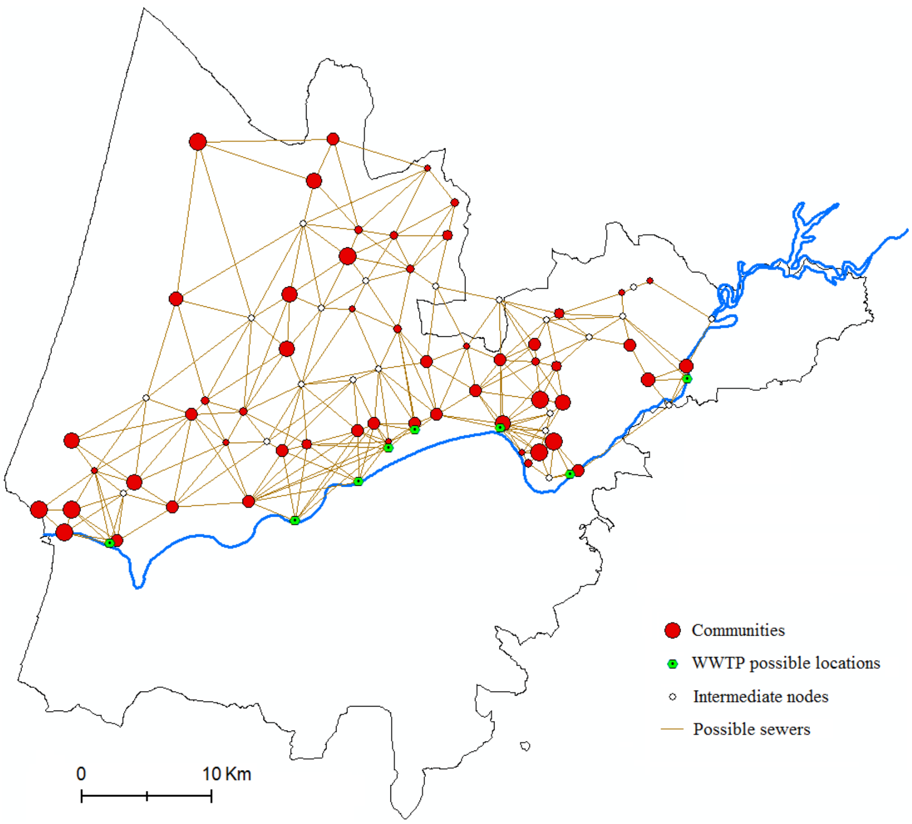


Figure 7.3 - Possible links for the installation of sewers

7.4.2. Population projection

A population projection was performed to estimate the amounts of wastewater that will occur during the future operations of the regional wastewater system. Instead of merely extrapolating the population of each community to the future or making subjective forecasts, we wanted to find patterns of a growth trend according to the characteristics of each area. These characteristics concern both the location, such as distance to major cities, and the resident population, in terms of quantity, density, age, employment and education. To keep the approach simple, the population projection was performed for the total population instead of components, since the data required for this study was only in terms of total population.

The aim of this population projection is to find the relation between the population growth rates (PGR) of the various communities in the region. Taking some past characteristics of a community as independent variables and considering the respective PGRs as dependent variables, a multiple regression analysis can be performed to investigate numerical relationships between them. This will establish a general expression for the value of the PGR of a community as a function of its characteristics. This expression can be applied afterwards to the current characteristics of the communities to use in the respective PGR in the future. With the projected PGR it is possible to determine the future population of each community, and thus the relevant demand for the regional wastewater system.

7.4.2.1. Multiple Regression Analysis

It would be ideal if the PGR of a community could be estimated by a simple equation using the community's own characteristics. Multiple regression analysis has been aimed at achieving this and it makes it possible to predict the dependent variable, PGR, by using several independent variables. The independent variables were chosen on the basis of groups of population characteristics of an area described by Murdock et al (1991), which yielded nine different features about the location of the communities and the resident population of the base period.

The multiple regression equation takes the following form:

$$PGR_{m,m+1} = a_0 + a_1 \times d^{cap} + a_2 \times d^{mun} + a_3 \times PGR_{m-1,m} + a_4 \times Pop_m + a_5 \times PD_m + a_6 \times MA_m \\ + a_7 \times UR_m + a_8 \times LR_m + a_9 \times AP_m + \varepsilon \qquad (7.23)$$

where $PGR_{m,m+1}$ is the population growth rate of the community for the decade corresponding to the target period, from the year m (launch year) to $m+1$ (target year); $a_0, \ldots, a_9$ are model coefficients; d^{cap} is the distance from the community to the capital of the region; d^{mun} is the distance from the community to the capital of the municipality; $PGR_{m-1,m}$ is the population growth rate of the community in the decade corresponding to the base period, from the year $m-1$ (base year) to m; Pop_m is the population of the community in year m; PD_m is the population density of the community in year m; MA_m is the mean age of the community in year m; UR_m is the unemployment rate of the community in year m; LR_m is the literacy rate of the community in year m; and AP_m is the economically active population rate of the community in year m.

The dependent variable considered for the analysis is the PGR of the target period, for each of the communities in the region. The regression coefficients *a* represent the amount the dependent variable changes when the corresponding independent variable changes 1 unit. The independent variables that do not increase the squared correlation coefficient by a significant amount can be removed from the equation during the computing of a statistical regression. It may be expected that the set of nine independent variables is reduced once the expression for the multiple regression has been obtained, as in the case study used in this chapter.

The multiple regression analyses were performed on the PGRs of the 106 communities in the Baixo Mondego study area. The data employed corresponds to the location of the communities and to the census data available for the populations in 1981, 1991 and 2001, represented by the values of *m-1*, *m* and *m+1* respectively. The general expression obtained is:

$$\begin{aligned} PGR_{m,m+1} &= 62.8024 - 0.7548 \times d^{mun} + 0.1856 \times PGR_{m-1,m} - 2.9052 \times PD_m \\ &- 1.4337 \times MA_m + \varepsilon \end{aligned} \tag{7.24}$$

Expression (7.24) was obtained after eliminating the variables for which the model coefficients were not significantly different from zero through (backward) stepwise regression analysis (Draper and Smith, 1998). It describes the PGR of a population in a decade starting at year *m* and ending at year *m+1* as a function of the several characteristics of the population in the previous decade, *m-1* to *m*. The adjusted squared correlation coefficient was 0.31, suggesting that there is a considerable error associated with the projection.

7.4.2.2. Scenario generation

Any projection for the future is inherently liable to a component of uncertainty, as in this population projection, through the error that arises from the multiple regression analysis. The characteristics of this error can be estimated when applying expression (7.24) to the past data of each community and comparing the PGR obtained with the growth that actually occurred. This will provide knowledge of the error obtained within the communities, represented by an average value and standard deviation. Assuming that the future error can be drawn from the same distribution as past error, it can be applied to improve future projections of the PGR. In particular, the characteristic of the error can be used to define a set of possible future scenarios.

For each of the 56 communities in the North Baixo Mondego study area, the data available from 1981 and 1991 were used to estimate the $PGR_{1991,2001}$. The values obtained for the $PGR_{1991,2001}$ by applying expression (7.24) were compared to the $PGR_{1991,2001}$ that actually occurred and is known. The resulting error follows a normal distribution with a mean value of -1.4885 and standard deviation of 8.9358. Note that the mean value would be 0 if it referred to all the communities of the Baixo Mondego region used in the regression analysis.

To estimate the $PGR_{2001,2021}$ of all the communities in the North Baixo Mondego study area, expression (7.24) was applied to the target period of 2001 to 2021. In order to consider the uncertainty corresponding to the error of the projection, the results obtained for the $PGR_{2001,2021}$ of each community have a value randomly added to them for the error that follows the same normal distribution as found for the past. In the end, the distribution of the error within all the communities in the future projection follows the normal distribution previously defined for the past. The resulting $PGR_{2001,2021}$ values of all the communities thus include the uncertainty component and correspond to a possible scenario. The repetition of this procedure allows the generation of different sets of values of $PGR_{2001,2021}$, corresponding to different scenarios. Taking into account the available data and with respect to the computational limitations, we assume that the uncertainty can be adequately captured using a set of 20 scenarios for the target year of 2021. Each scenario is considered to have the same probability of occurrence, p_s, equal to 1/20. The values of the $PGR_{2001,2021}$ are used to calculate the population of each community, as required to estimate the respective amounts of wastewater in each scenario of the case study.

7.4.3. Infrastructure costs

The cost of the wastewater system of the solution of a scenario is composed of the amortization of the capital cost and the annual operating (and maintenance) costs:

$$C_s = CC + CO_s \times \beta\,, \qquad s \in \boldsymbol{S} \tag{7.25}$$

where CC are capital costs, CO_s are operating costs for scenario s; and β is the discount factor with 4 per cent interest over a period of 20 years.

Each of these costs is related to each of the facilities and is defined as follows:

$$CC = \sum_{i \in N_S \cup N_I} \sum_{j \in N} \left(CC1_{ij} x_{ij} + CC2_{ij} y_{ij} \right) + \sum_{k \in N_T} \sum_{p \in T} CC3_{kp} z_{kp} \tag{7.26}$$

$$CO_s = \sum_{i \in \boldsymbol{N_S} \cup \boldsymbol{N_I}} \sum_{j \in \boldsymbol{N}} \left(CO1_{ijs} x_{ij} + CO2_{ijs} y_{ij} \right) + \sum_{k \in \boldsymbol{N_T}} \sum_{p \in \boldsymbol{T}} CO3_{kps} z_{kp} \,, \qquad s \in \boldsymbol{S} \tag{7.27}$$

where $CC1_{ij}$ is the capital cost for the sewer linking node i to node j; $CC2_{ij}$ is the capital cost for the pumping station elevating wastewater from node i to node j; $CC3_{kp}$ is the capital costs for the treatment plant of type p at node k; $CO1_{ijs}$ is the operating cost in scenario s for the sewer linking node i to node j; $CO2_{ijs}$ is the operating cost in scenario s for the pumping station transporting wastewater from node i to node j; and $CO3_{kps}$ is the operating cost in scenario s for the treatment plant of type p at node k.

7.4.4. Results for individual scenarios

Once the geographic data for the case study has been collected it is possible to obtain a minimum-cost solution for the wastewater system of the region in each future population scenario in 2021. This is done using the general deterministic wastewater system planning model presented in Chapter 3 and referred to earlier in this chapter. The assessment of the water quality of the river is taken into account by stipulating a maximum WWTP coverage capacity of 150 thousand inhabitants. The SA algorithm and LI procedure previously described were used, and each scenario of the case study was solved for 20 different random seeds of the SA. Table 7.1 shows the cost of the solution for each of the 20 scenarios. The capital cost *CC* ranged between 28.36 M€ and 30.88 M€, and the total discounted cost of the solution, *C* ranged between 39.73 M€ and 43.79 M€. The variations between the minimum and maximum value within the scenarios were 8% and 9%, respectively. An example of the configuration of a solution is shown in Figure 7.4, through a three-dimensional view of the minimum cost solution of scenario 5, the lowest cost scenario. The computation time taken to solve the deterministic model for the case study was around 1 minute for each scenario. The values obtained for the minimum costs of each individual scenario are used as variables in the different model approaches of the present case study.

Table 7.1 - Values for the minimum cost solution of each scenario

	Deterministic model		
Scenario	CC (M€)	CO_s (M€/year)	C_s (M€)
1	28.64	0.87	40.49
2	28.62	0.87	40.44
3	29.48	0.89	41.60
4	29.16	0.89	41.23
5	28.36	0.84	39.73
6	29.49	0.91	41.80
7	29.75	0.91	42.12
8	28.51	0.86	40.25
9	28.49	0.88	40.44
10	28.51	0.87	40.37
11	29.08	0.89	41.23
12	30.32	0.94	43.06
13	29.46	0.89	41.62
14	29.75	0.91	42.12
15	30.28	0.93	42.92
16	28.62	0.86	40.34
17	29.29	0.89	41.43
18	29.25	0.89	41.34
19	30.88	0.95	43.79
20	28.96	0.89	41.01

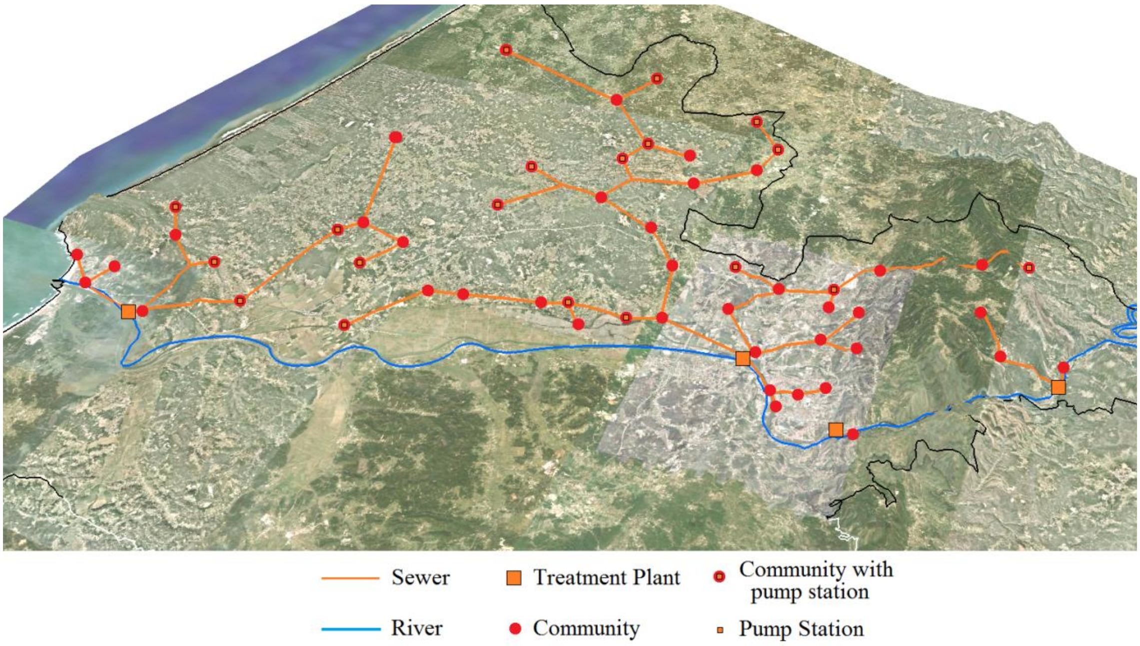


Figure 7.4 - 3D view of a minimum cost configuration for scenario 5 of the case study

7.5. Results and discussion

7.5.1. Results for minimization of the expected regret

The optimization model of expected regret minimization was applied to the case study. The solution for this approach is designed to be completely reliable and thus is feasible in any scenario, even the worst-case scenarios. The results obtained for capital cost and overall cost are shown in Table 7.2, together with the results of the other approaches. The robust solutions have a single *CC*, corresponding to the capital cost of the infrastructure. The value for C_s includes the discounted operating cost and depends on the scenario that occurs in the future. For the minimization of the expected regret, CC = 31.96 M€, and C_s varies from 44.25 M€ to 45.16 M€, which is about a 2.0% variation. The values of C_s are from 3.0% to 10.2% higher than the minimum cost solution of each scenario (Table 7.1). These differences correspond to the regret. The optimal configuration of the wastewater system for this model is displayed in Figure 7.5. In the solution obtained, seven treatment plants are installed, two of which receive a large proportion of the discharges. The solution requires the installation of nineteen pumping stations, and the total length of the sewers is around 180 km.

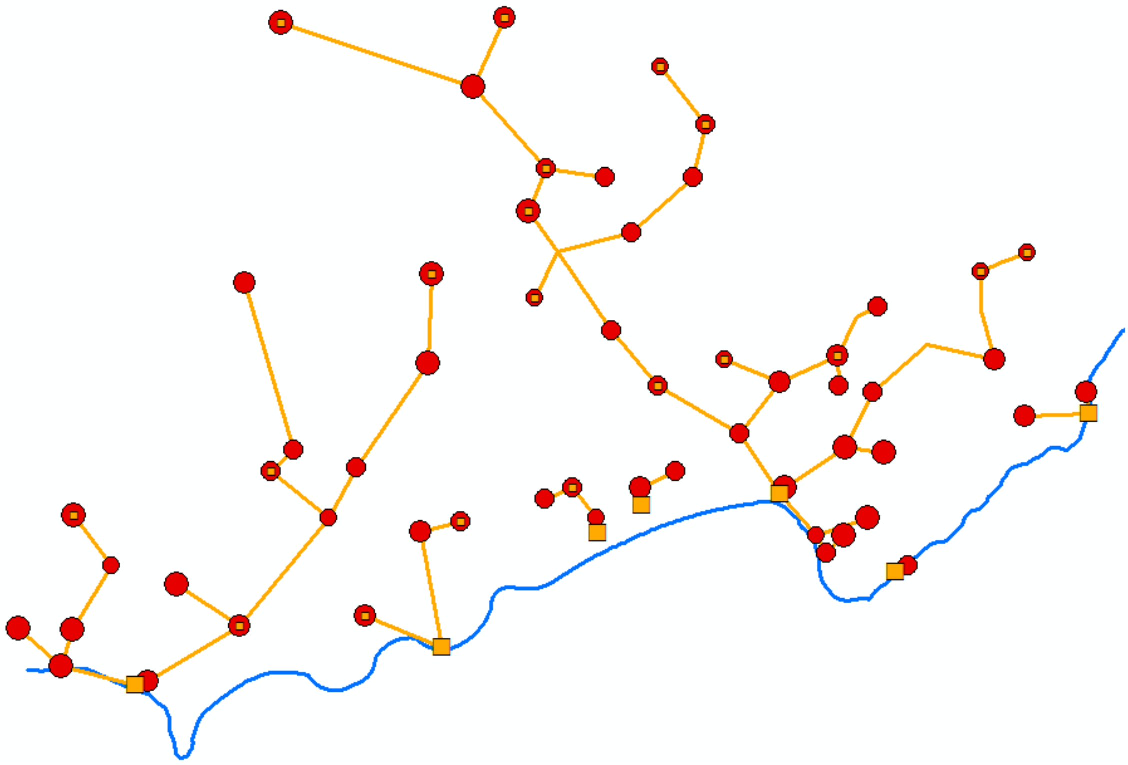


Figure 7.5 - Optimal configuration for minimization of the expected regret

7.5.2. Alpha-reliable expected regret

7.5.2.1. α-reliable

The α-reliable model of expected regret minimization was applied to the case study, considering a reliability value of α = 0.90. The reliability set implies that the facilities are designed to work in perfect conditions in at least 90% of the scenarios. This solution disregards the 10% of the scenarios that most negatively influence the objective function. These here correspond to two worst-case scenarios, where some facilities are undersized, and the solution for the wastewater treatment system may become infeasible. The results for capital cost and overall cost are shown in Table 7.2. The robust solution has a CC = 31.21 M€ and, depending on the scenario, C_s varies from 43.19 M€ to 43.97 M€, which is about a 1.8% variation. The values of C_s are from 2.4% to 8.0% higher than the minimum cost solution of each scenario (Table 7.1). These differences correspond to the regret. The optimal configuration of the wastewater system for this model is displayed in Figure 7.6. In the solution obtained, four treatment plants are installed, two of which receive a large proportion of the discharges. The solution requires the installation of twenty-one pumping stations and the total length of sewers is around 188 km. The two scenarios that are excluded from the reliability set are those that had the most expensive minimum cost solution, which would not necessarily indicate that they would make the largest contribution for the expected regret.

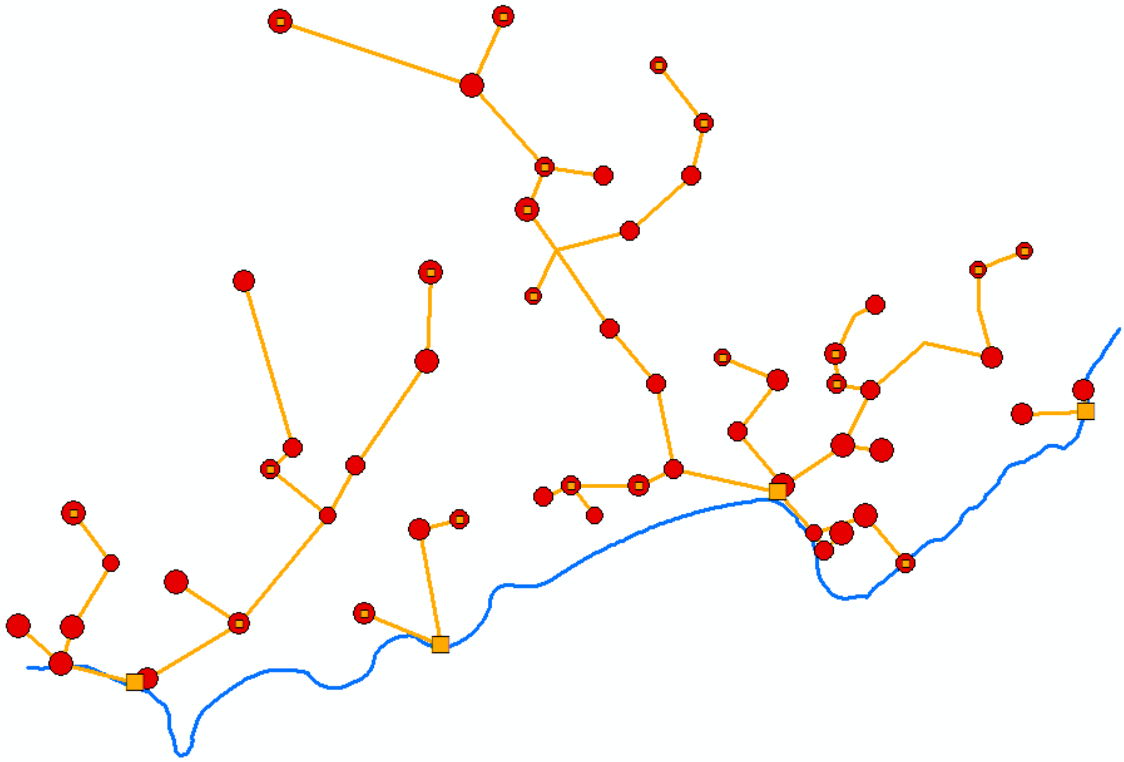


Figure 7.6 - Optimal configuration for alpha-reliable model with α = 90%

7.5.2.2. a'-reliable

The α'-reliable model of expected regret minimization was applied to the case study, considering a value of α' = 0.75. Therefore, the reliability set for the sewer's behavior implies that each sewer is designed to work in perfect conditions in at least 75% of the scenarios. In the remaining 25% of the scenarios the sewer might not work perfectly, but the overall solution for the wastewater treatment system is still feasible. The results for capital cost and overall cost are shown in Table 7.2. The robust solution has a CC = 31.72 M€ and, depending on the scenario, C_s varies from 44.03 M€ to 44.93 M€, which is about a 2.0 % variation. The values of C_s are from 2.5% to 9.8% higher than the minimum cost solution of each scenario (Table 7.1). These differences correspond to the regret. The optimal configuration of the wastewater system for this model is displayed in Figure 7.7. In the solution obtained, seven treatment plants are installed, two of which receive a large proportion of the discharges. The solution requires the installation of nineteen pumping stations, and the total length of sewers is around 178 km. The sewers in brown are those that are not contained in the reliability set, and therefore might work under undesirable conditions for some scenarios.

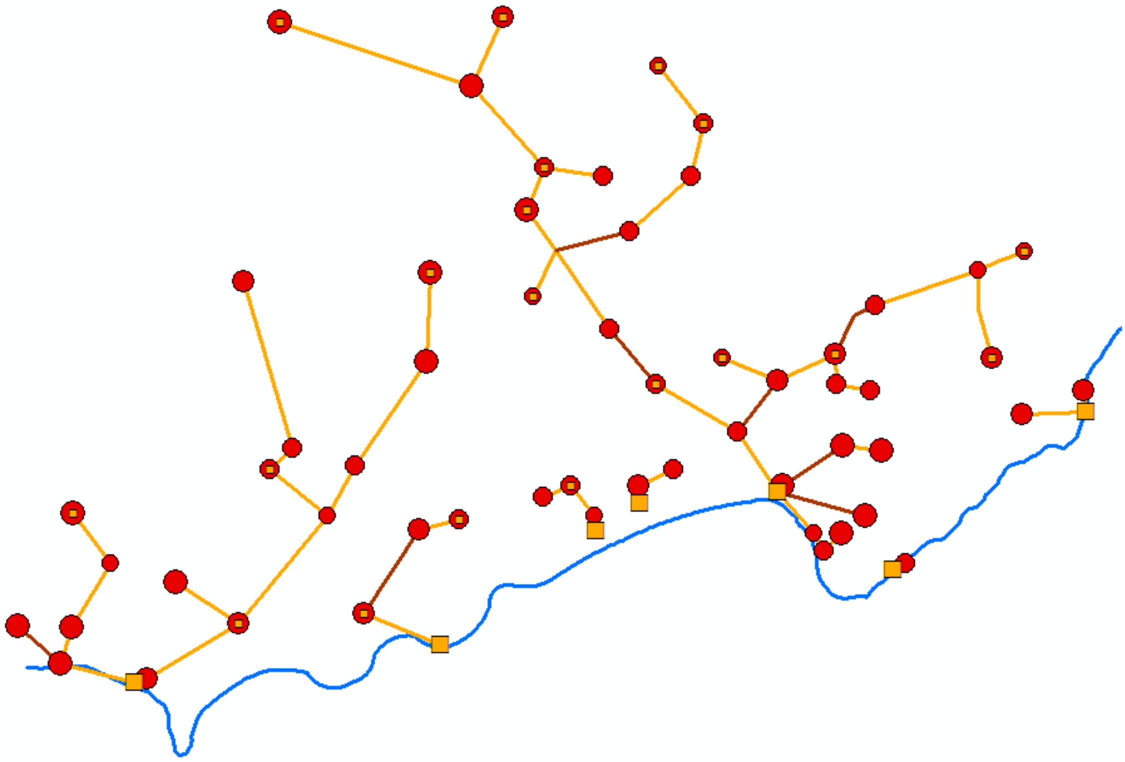


Figure 7.7 - Optimal configuration for the alpha-reliable model with α' = 75%

7.5.3. Comparison of results

For better reliability of the solution, the cost increases both for the *CC* and the C_s. The expected regret minimization model is a special case of the alpha-reliable expected regret in which α =1.0 and α' =1.0, that is, complete reliability for the whole wastewater system in all the scenarios. The solution for α = 90% has both a *CC* and the C_s around

2.4 % lower than that obtained from the minimization of the expected regret. The solution for *α'* = 0.75 has a *CC* around 0.8% lower and the C_s on average 0.5% lower than that obtained from the minimization of the expected regret. Despite *α'* = 0.75 being a lower reliability set, the *α'* is only applied to the sewers and its regret is computed over the whole set of scenarios, while for *α* = 90%, 10% of the scenarios are disregarded. Therefore, the solution for *α* = 90% has a *CC* around 1.6% lower and the C_s on average 1.9% lower than for *α'* = 0.75. But there is a risk associated with these cost reductions, particularly for the α-reliable solution, which does not guarantee that the system will work properly if worst-case scenarios occur.

Table 7.2 - Solutions of the different models

	Minimization of the expected regret		Alpha-reliable			
			α = 90%		α' = 75%	
Scenario	*CC*	C_s	*CC*	C_s	*CC*	C_s
1	31.96	44.52	31.21	43.45	31.72	44.30
2		44.50		43.46		44.27
3		44.72		43.65		44.50
4		44.66		43.59		44.43
5		44.25		43.19		44.03
6		44.81		43.74		44.58
7		44.88		43.83		44.69
8		44.44		43.38		44.23
9		44.57		43.50		44.33
10		44.52		43.46		44.30
11		44.66		43.59		44.44
12		45.07		-		44.84
13		44.79		43.70		44.54
14		44.93		43.85		44.69
15		45.06		43.97		44.83
16		44.41		43.33		44.18
17		44.71		43.64		44.47
18		44.72		43.65		44.50
19		45.16		-		44.93
20		44.61		43.57		44.41

With respect to the configurations of the solutions, the design for the solution with complete reliability is not very different from the solution for α' = 75%. For the latter the layout of some sewer networks is straighter and shorter, since more wastewater is allowed to be directed to some sewers without having to increase the pipe diameter. For the configuration of the solution for α = 90%, the major difference is the reduction in the number of treatment plants from seven to four. This happened because the largest WWTP in the region, located near Coimbra, was near the maximum capacity in the other solutions. By excluding two scenarios from the reliability set, that treatment plant is able to receive the wastewater generated in more communities, avoiding the construction of three other treatment plants. This implies a longer sewer network and the installation of more pumping stations, but the cost is lower because of the the savings on the WWTPs. The computation time taken to solve the models for the case study was around 20 minutes for the minimization of the expected regret and the α'-reliable model, but increased to around 4.5 hours for the α-reliable model.

7.6. Conclusion

An optimization-based approach for the planning of a robust regional wastewater system has been outlined. The planning of these systems is complex in itself, but it becomes even harder when considering the uncertainties in the problem. In this chapter, the uncertainty in the system's future amounts of wastewater was taken into account, derived from the population projection for the target year of 2021. This uncertainty is considered to be represented through a set of scenarios. The approach aims to find a robust solution that will perform well under all possible scenarios. An optimization model was used to minimize the expected regret, defined in terms of the overall cost of the solution to be adopted. Two variations of the model were defined according to the alpha-reliable concept.

A case study based on a real world situation from Baixo Mondego, a European NUTS III region in Portugal, was used to illustrate the procedure. The results showed that, with a reasonable cost increase, is possible to obtain a configuration that is designed to meet the set of possible future demands. When the reliability of the system is allowed to be reduced by disregarding some worst-case scenarios, lower cost solutions can be found, but with a certain risk associated with failures in some facilities.

Some open issues deserve further investigation. For instance, the reliability set in the alpha-reliable model is evaluated through a complete enumeration method that will need to be improved if different values for α and different sets of probabilities are required. Some assumptions and several simplifications were considered in the case study data, which are reasonable in the academic world but could be enhanced in a more specific approach. However, the robust optimization approach presented here has shown promising results that could be applied to other variations of the same problem or other similar problems. The uncertainty in other variables of the regional wastewater system planning might also be considered.

Chapter 8

OptWastewater: a computer program for regional wastewater system planning

8.1. Introduction

The wastewater generated in urban areas is one of the main sources of water pollution. The impact of wastewater is particularly hazardous when the discharges are made without any treatment. In Portugal around 30% of the population is not provided with any wastewater treatment system. This is one of the main reasons why none of the selected surface water quality measuring points installed around the country scored the highest classification last year, and 12% even had the worst level of the five water quality levels defined by the Portuguese National Information System of Water Resources (SNIRH). The aim to reach a good quality for all water bodies was revitalized by the European Union through the adoption of the Water Framework Directive. Anyhow, efficient wastewater systems are crucially important to the promotion of a sustainable development.

Since wastewater systems can be very expensive, they should be planned efficiently, taking into account not only the costs but also the quality of the receiving water bodies. The infrastructure for treating wastewater includes the following facilities: wastewater treatment plants (WWTP) to process the wastewater before it is discharged into rivers; sewer networks connecting the population centers with the WWTP; and pump stations to lift wastewater if it is unfeasible or uneconomic to drain it by gravity. Even though wastewater systems are often planned at local level, planning at a regional level can provide more economically and/or environmentally advantageous solutions. Because of the very large number of available configurations, it would usually be ineffective to evaluate each one individually to find an optimal solution. But this task is greatly facilitated and made efficient if decision-aid tools that make use of optimization models are employed.

OptWastewater, an easy-to-use computer program developed for regional wastewater system planning, is presented in this chapter. The computer code was written in Visual Basic, thereby offering all the user-friendliness of a typical Windows application. The chapter is organized as follows. In the next section the planning approach upon which *OptWastewater* is built is explained. Then the *OptWastewater* program is presented, including all the modules to input the data, solve the model, and output the results. Then an application of *OptWastewater* to some cases is described. Finally, in the closing section some concluding remarks are presented.

8.2. Planning approach

The regional planning of wastewater systems requires both the drainage of the wastewater generated by the population centers of a region and the meeting of the quality standards defined for the river that receives the wastewater.

The aim of regional wastewater system planning is to determine an optimal solution for the layout of the sewer network, and for the location, type, and size of the pump stations and WWTP to include in the system. This search for the best regional wastewater system can only be efficient if pursued through optimization models, since the number of available configurations is far too large to enable individual evaluation. The first optimization model that initiated the present line of research pursued by the authors was introduced by Sousa et al. (2002) and consisted of a deterministic approach with a cost-minimization objective. An improved version of the wastewater system planning optimization model was developed and described by Chapter 3. In Chapter 5 this model was extended to a multi-objective version to handle the presence of environmental objectives. Recently, a robust optimization model has been developed to consider the presence of uncertainty in the flow of the river or in the population centers of the region. The objective function of these models is subjected to different constraints to ensure that the sewer network will be sized according to hydraulic laws and regulations. Constraints to ensure that the treated wastewater discharged from each WWTP will not create environmental damage have also been considered. The water quality standards defined for the river can be evaluated according to environmental parameters such as dissolved oxygen (DO), biochemical oxygen demand (BOD), nitrogen (N), and phosphorus (P).

The *OptWastewater* program incorporates the latest optimization models developed in this line of research: a single-objective optimization model; a multi-objective optimization model; and a robust optimization model. This chapter introduces two important innovations that were not dealt with in the previous works about these optimization models. The first innovation is the possibility of considering the presence of one or more affluents to the main river. These affluents may be tributary streams or the discharge of an extra wastewater source, such as an industrial discharge or a WWTP of a complementary system. The other innovation is the ability to consider the presence of previously existing facilities. When the size of such facilities is equal to or larger than what is required in a considered solution, only the operating and maintenance cost is taken into account in the cost calculations. Otherwise, the expansion of pump stations and WWTP is allowed, subject to a certain partial capital cost.

8.3. The OptWastewater program

OptWastewater has been developed in the Windows environment, using the language Visual Basic. The program was designed in a modular way so that the code may easily be adapted to the needs of future improvements. The main modules correspond to the type of optimization model used, and define how the different modules and respective subroutines of the problem are related. Figure 8.1 shows these main modules on the left. The diagram on the right shows the different modules and how these are connected. The modules containing an inner hexagon refer to those that vary in some subroutines according to the main module used. In the subsections that follow the *OptWastewater* program and its modules are described for the application to a small example.

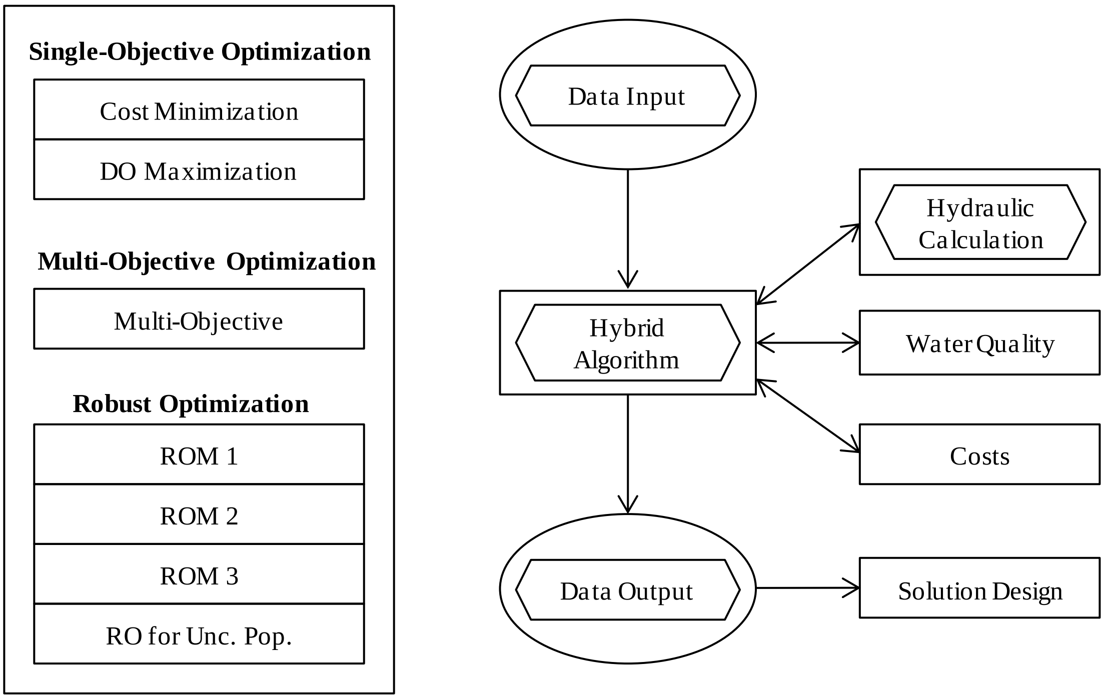


Figure 8.1 - The relation between *OptWastewater* modules

8.3.1. Example

A small example to mimic a real-world situation is used in this chapter to show the application of the *OptWastewater* program. The region depicted in Figure 8.2 has a rectangular shape, with a length of 50 km along the main river and 25 km in the perpendicular direction. Different nodes are used to set a grid that represents the topography of the region according to local heights. Population centers are located in some nodes of the grid, while the sewers that collect the wastewater from these population centers can be connected from each node to one of the neighboring nodes. In this example, the maximum height is 200 m and the maximum population of a center is 50,000 inhabitants. The total population of the region is 150,000 inhabitants. The example considers the presence of a main river, with a flow of 3 m^3/s, and a tributary river, with a flow of 1 m^3/s. A previously existing system composed of three sewers and one WWTP is taken into consideration for searching for the minimum cost solution of the regional wastewater system. The water quality of the river is restricted to having a minimum DO concentration of 7.5 mg/l.

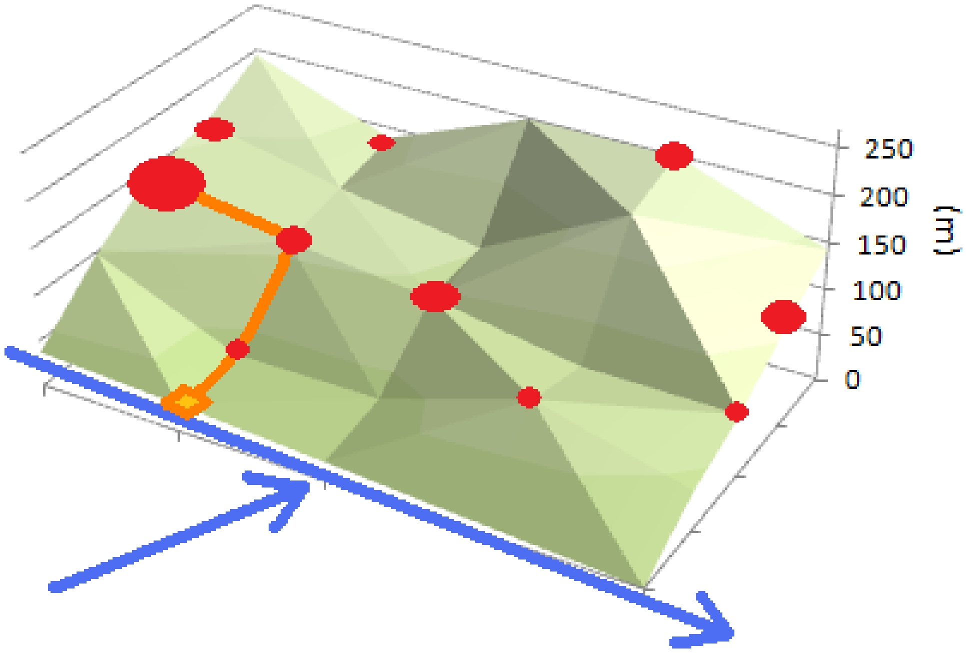


Figure 8.2 - Example

8.3.2. Entering and Main Modules

When opening the *OptWastewater* program file, the user is directed to an Entrance Window as shown in Figure 8.3. In this window there is the opportunity to select from three approaches, relating to the main modules presented in Figure 8.1. If the *Single-Objective Optimization* approach is selected the problem can be solved with an objective function of cost minimization or DO maximization. The *Multi-Objective Optimization* approach involves an objective function with three different objectives:

minimization of capital cost; minimization of operating and maintenance costs; and maximization of DO. Here the user is allowed to define the weight given to each objective, since the model is solved through the weighting method. The *Robust Optimization* approach is used to deal with uncertainties in the problem, either in the flow of the river or in the population of the centers of the region. When the uncertainty in river flows is selected, the user can choose from 3 RO models: ROM1, ROM2, and ROM3.

Figure 8.3 - *OptWastewater* Entrance Window

In this chapter we will focus on the *Single-Objective Optimization* approach, since its optimization model is the most used and its interpretation is easiest to describe. After selecting the *Single-Objective Optimization* in the entrance window, a dialog box is presented to select either the objective function of cost minimization or DO maximization. When selecting cost minimization, which will be used in this presentation, the user is directed to the *Main Window*, shown in Figure 8.4.

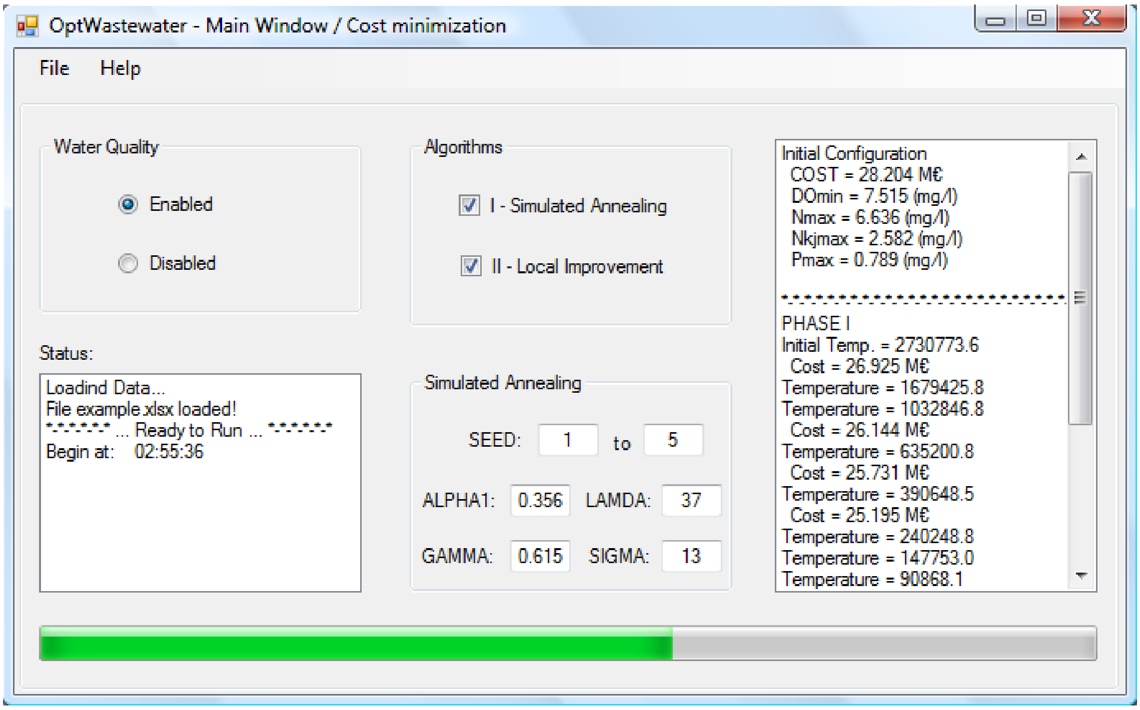


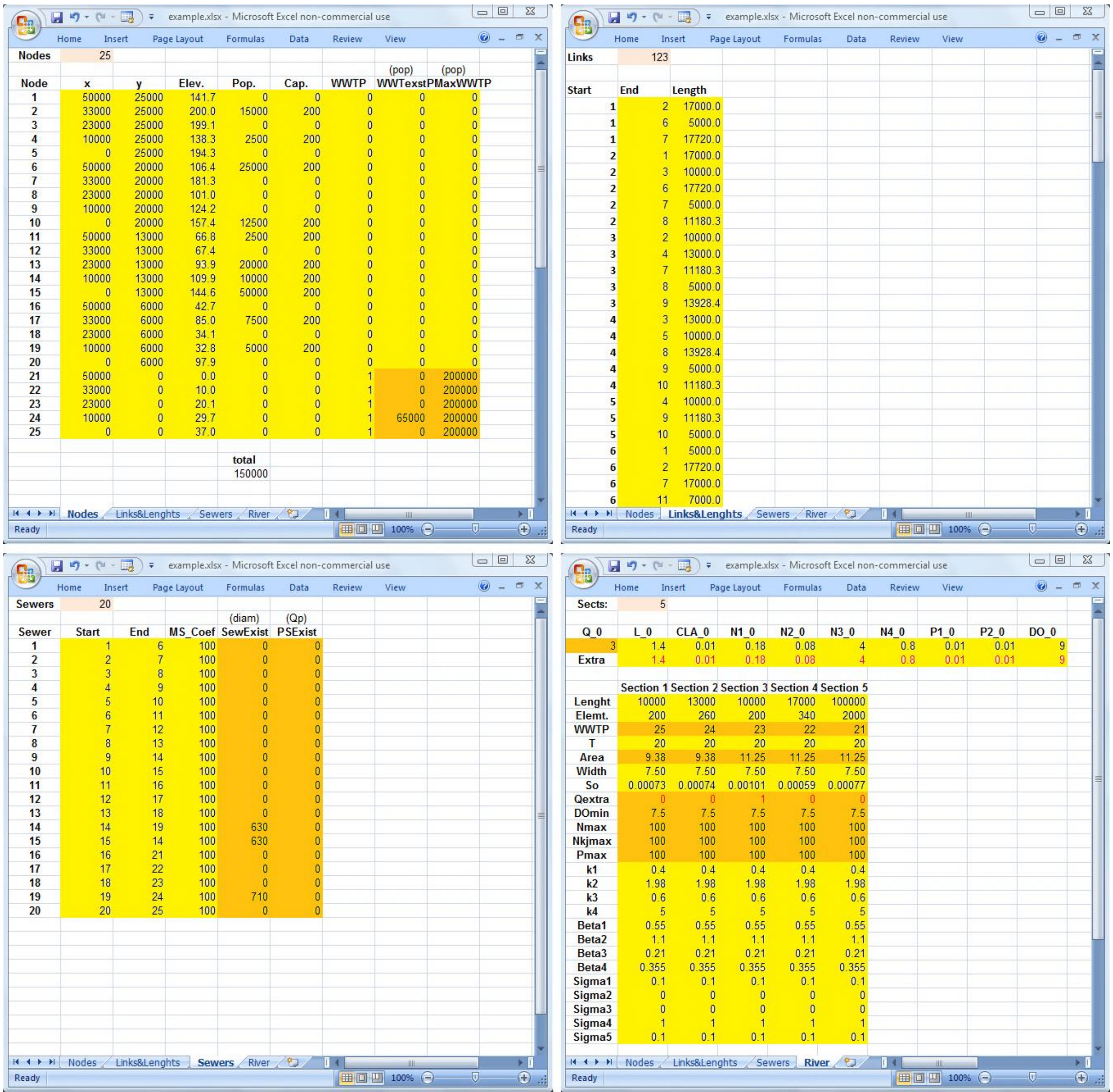
Figure 8.4 - Single-Objective Optimization – Main Window for Cost minimization

The *Main Window* is composed of different boxes. When the window opens, the only enabled feature is the *Water Quality* group box, to choose whether the problem being studied will be analyzed considering/not considering the water quality in the river. After this selection, the File tab in the menu bar is enabled. This tab allows inputting data into the program, running the program, viewing the solution configuration, saving the results or simply quitting the program. The remaining elements in the window become enabled after the data input and program run are executed. The *Status* text list, on the left, displays the current status of the program. In the middle of the window there are two group boxes relating to the algorithms selected. In the *Algorithms* group box users can select which algorithms they want to use by means of check boxes. If the simulated annealing is elected, the *Simulated Annealing* group box becomes enabled, allowing definition of the parameters for the simulated annealing. When no algorithm is selected, the program run will present the results for the initial configuration given by the input data. Finally, the right text list shows the main results obtained while running the program, while a progress bar at the bottom of the window shows the progress of the optimization model.

8.3.3. Input Description

The first step for solving a regional wastewater system is to collect all the required information about the problem. This is done through the use of an Excel workbook with four sheets, as shown in Figure 8.5. The first sheet (top left) has the information about each node. The first column contains the node enumeration, the second and third columns contain the coordinates of the nodes. Then there are columns with information about the elevation, population and respective per capita wastewater generation rate of each node. The last three columns contain information about the WWTP: if the node is of the WWTP type, the respective cell has value 1; if there is an existing WWTP in the node, the maximum capacity in terms of inhabitants is given in the next column; the last column contains the maximum capacity of a possible WWTP in the respective node, whether it is new or results from the expansion of an existing one. The maximum discharge in each plant is usually defined to guarantee the quality standards that must be met in the river. The second sheet (top right) contains the information about all the possible sewers between the nodes, with information about the starting node, the end node, and the length in meters. The third sheet (bottom left) contains the information about the initial solution. Start nodes and end nodes are specified, and there is a specific column to identify the Manning-Strickler coefficient of any possible sewer that starts in those nodes. Note that only one sewer can start in each node. The last two columns in this sheet relate to the diameter of possible existing sewers and the peak flow of any pump station existing in that node. The last sheet (bottom right) is used only when the water quality model in the river is enabled, and contains all the data on the river(s). The first rows contain information about the initial characteristics of the main river and tributaries, particularly relating to the water quality parameters and the flow of the main river. The rows underneath contain information about each river reach, such as the length, the number of elements considered, the respective node of the WWTP, temperature, transversal area, transversal width, slope, and flow of the tributary that discharges in that reach. Then, the subsequent four rows define the minimum or maximum values for the water quality parameters: DO, total N, Kjeldahl nitrogen (NKj) and total P. The remaining rows define secondary parameters used in the water quality model.

After editing all the correct information in the Excel workbook, the data input module in the program can be executed using *File > Open* in the menu bar. A dialog box is presented to select the respective **.xls* or **.xlsx* file. This step enables *File > Configuration* in the menu bar to allow viewing the initial solution configuration, and also enables *File > Run* to allow the program run to be executed.



Nodes	25							
							(pop)	(pop)
Node	x	y	Elev.	Pop.	Cap.	WWTP	WWTexst	PMaxWWTP
1	50000	25000	141.7	0	0	0	0	0
2	33000	25000	200.0	15000	200	0	0	0
3	23000	25000	199.1	0	0	0	0	0
4	10000	25000	138.3	2500	200	0	0	0
5	0	25000	194.3	0	0	0	0	0
6	50000	20000	106.4	25000	200	0	0	0
7	33000	20000	181.3	0	0	0	0	0
8	23000	20000	101.0	0	0	0	0	0
9	10000	20000	124.2	0	0	0	0	0
10	0	20000	157.4	12500	200	0	0	0
11	50000	13000	66.8	2500	200	0	0	0
12	33000	13000	67.4	0	0	0	0	0
13	23000	13000	93.9	20000	200	0	0	0
14	10000	13000	109.9	10000	200	0	0	0
15	0	13000	144.6	50000	200	0	0	0
16	50000	6000	42.7	0	0	0	0	0
17	33000	6000	85.0	7500	200	0	0	0
18	23000	6000	34.1	0	0	0	0	0
19	10000	6000	32.8	5000	200	0	0	0
20	0	6000	97.9	0	0	0	0	0
21	50000	0	0.0	0	0	1	0	200000
22	33000	0	10.0	0	0	1	0	200000
23	23000	0	20.1	0	0	1	0	200000
24	10000	0	29.7	0	0	1	65000	200000
25	0	0	37.0	0	0	1	0	200000
				total				
				150000				

Links	123	
Start	End	Length
1	2	17000.0
1	6	5000.0
1	7	17720.0
2	1	17000.0
2	3	10000.0
2	6	17720.0
2	7	5000.0
2	8	11180.3
3	2	10000.0
3	4	13000.0
3	7	11180.3
3	8	5000.0
3	9	13928.4
4	3	13000.0
4	5	10000.0
4	8	13928.4
4	9	5000.0
4	10	11180.3
5	4	10000.0
5	9	11180.3
5	10	5000.0
6	1	5000.0
6	2	17720.0
6	7	17000.0
6	11	7000.0

Sewers	20				
				(diam)	(Qp)
Sewer	Start	End	MS_Coef	SewExist	PSExist
1	1	6	100	0	0
2	2	7	100	0	0
3	3	8	100	0	0
4	4	9	100	0	0
5	5	10	100	0	0
6	6	11	100	0	0
7	7	12	100	0	0
8	8	13	100	0	0
9	9	14	100	0	0
10	10	15	100	0	0
11	11	16	100	0	0
12	12	17	100	0	0
13	13	18	100	0	0
14	14	19	100	630	0
15	15	14	100	630	0
16	16	21	100	0	0
17	17	22	100	0	0
18	18	23	100	0	0
19	19	24	100	710	0
20	20	25	100	0	0

Sects:	5								
Q_0	L_0	CLA_0	N1_0	N2_0	N3_0	N4_0	P1_0	P2_0	DO_0
3	1.4	0.01	0.18	0.08	4	0.8	0.01	0.01	9
Extra	1.4	0.01	0.18	0.08	4	0.8	0.01	0.01	9

	Section 1	Section 2	Section 3	Section 4	Section 5
Lenght	10000	13000	10000	17000	100000
Elemt.	200	260	200	340	2000
WWTP	25	24	23	22	21
T	20	20	20	20	20
Area	9.38	9.38	11.25	11.25	11.25
Width	7.50	7.50	7.50	7.50	7.50
So	0.00073	0.00074	0.00101	0.00059	0.00077
Qextra	0	0	1	0	0
DOmin	7.5	7.5	7.5	7.5	7.5
Nmax	100	100	100	100	100
Nkjmax	100	100	100	100	100
Pmax	100	100	100	100	100
k1	0.4	0.4	0.4	0.4	0.4
k2	1.98	1.98	1.98	1.98	1.98
k3	0.6	0.6	0.6	0.6	0.6
k4	5	5	5	5	5
Beta1	0.55	0.55	0.55	0.55	0.55
Beta2	1.1	1.1	1.1	1.1	1.1
Beta3	0.21	0.21	0.21	0.21	0.21
Beta4	0.355	0.355	0.355	0.355	0.355
Sigma1	0.1	0.1	0.1	0.1	0.1
Sigma2	0	0	0	0	0
Sigma3	0	0	0	0	0
Sigma4	1	1	1	1	1
Sigma5	0.1	0.1	0.1	0.1	0.1

Figure 8.5 - Input – Excel Sheets

8.3.4. Model Solving

Wastewater system planning optimization models incorporate discrete variables and non-linear functions, and, due to the complexity involved in mixed-integer non-linear optimization, they require heuristic algorithms to solve them. A hybrid algorithm composed of a combination of a simulated annealing algorithm (SA) and a local improvement procedure (LI) has been used as the solution method for these optimization models. More information about this algorithm and its implementation can be found in Kirkpatrick (1983) and Chapter 4.

The hybrid algorithm is contained in the crucial model-solving module of the program. This module contains several sub-routines that are used according to the optimization model selected. The hybrid algorithm module is linked to three modules required to evaluate the solutions for each iteration of the algorithm: hydraulic calculation; water quality; and cost. The hydraulic calculation module is used to size sewers, possible pump stations and the WWTP, complying with all relevant regulations. The water quality module contains a specific model used to evaluate the effects of wastewater discharges in the river. This water quality model evaluates the water quality parameters of the river, taking into consideration the following factors: atmospheric reaeration, photosynthesis, respiration, sediment oxygen demand, carbonaceous organic matter oxidation, and nitrification. The cost module is used to calculate the capital costs and the discounted maintenance and operation costs of all facilities associated with the solution. The cost of the wastewater system facilities was taken from a sample of Portuguese case studies.

The program makes use of the model-solving modules to solve the optimization model selected and can be executed by selecting *File* > *Run* in the menu bar of the *Main Window.*

8.3.5. Output Description

After the program has been run and the best solution for the wastewater system is obtained, the user can check the main results in the text list on the right of the *Main*

Window. The final configuration can then be viewed through *File* > *Configuration* in the menu bar, resulting in a *Solution Configuration Window* like that in Figure 8.6. When clicking the button *Design* in this window, a graphic image of the solution is shown, relating to the initial solution, the solution obtained from the SA algorithm or the final solution. If the user wants to have an idea of the terrain of the solution, the *Contour* button will provide it by drawing some points containing groups of elevation values according to the steps selected. These points can be connected in any graphics painting program to achieve the contour lines representing the land relief. The graphics image can be saved by clicking in the *Save* button, which shows a dialog box to select a name for the new **.bmp* or **.jpg* file.

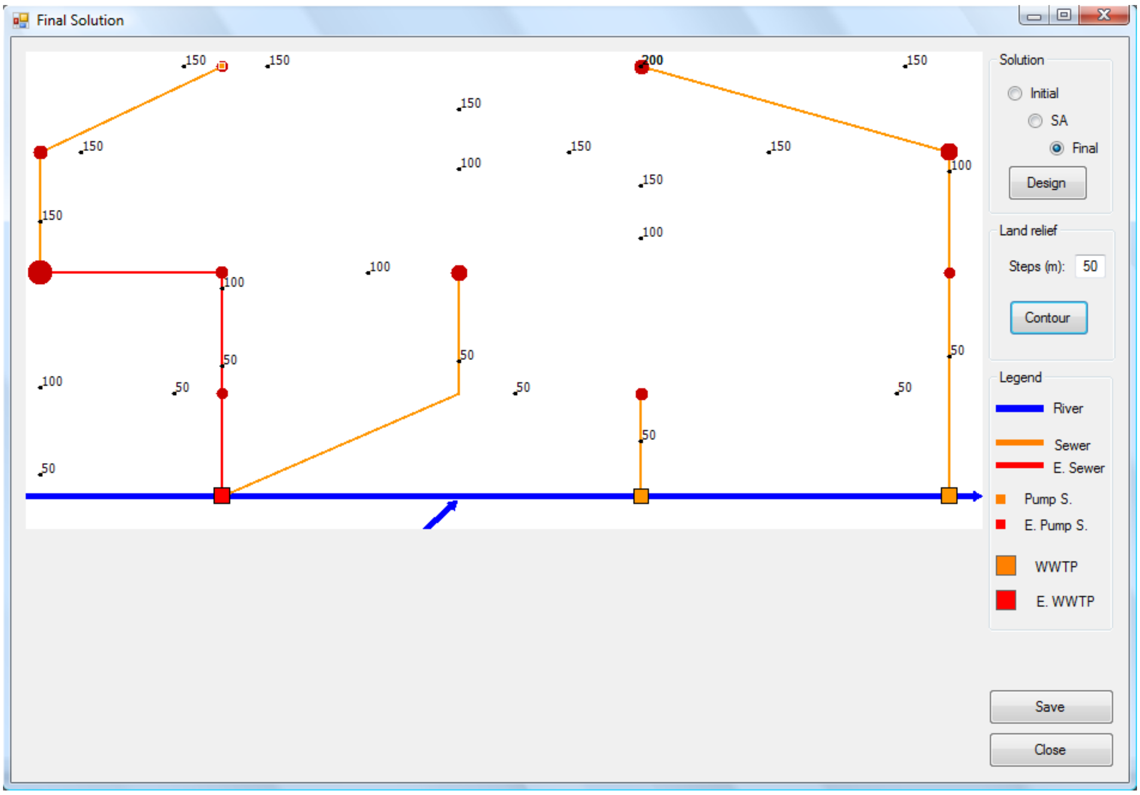
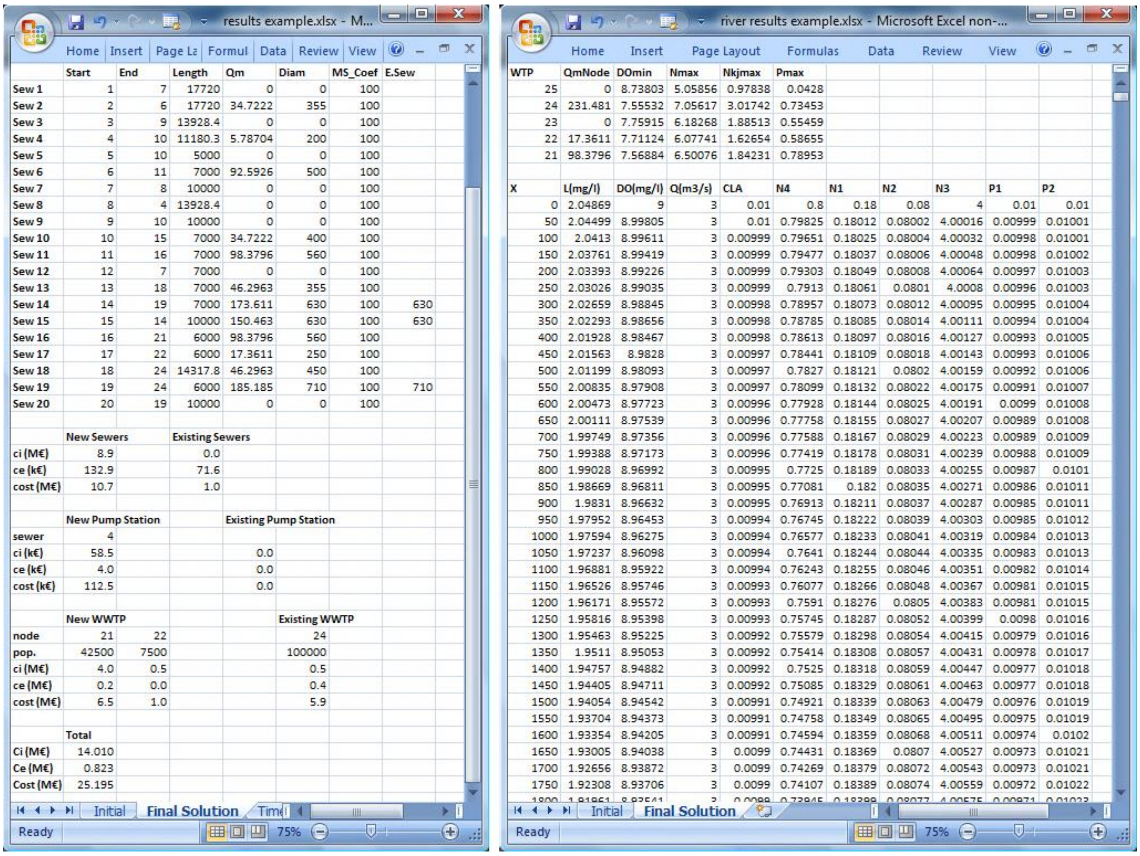


Figure 8.6 - Solution Configuration Window

All the information about the results is provided in an excel file that is stored in a single Excel workbook through the link *File > Save* in the menu bar of the *Main Window*. A dialog box requiring the name for the new **.xls* or **.xlsx* file to save is presented. The Excel workbook has three sheets: the first has the output for the initial solution, the second has the output for the final solution, and the third contains information about the parameters used and the time taken by the program to find the optimum solution. For the second sheet, describing the final solution (Figure 8.7 - left), the first group of lines show all the information on the resulting sewers: start node, end node, length, average flow, diameter of the sewer, Manning-Strickler coefficient, and diameter of the previously existing sewer. The rows below contain the cost of the different components of the system, and for the system as a whole. These costs are divided into capital costs, operating and maintenance costs, and total costs, for both the new and existing facilities.

When the water quality is enabled, a second Excel workbook is saved which contains information about the river. The first sheet of the file contains a summary of the input data. In the second sheet (Figure 8.7 - right) the river flow and the water quality characteristics are presented. In the first rows, for each river reach, the discharged flow (in l/s) of the respective WWTP is presented, as well as the minimum DO, and the maximum N, Nkj and P for that reach. The remaining rows give several water quality concentrations, and their number may be very high since they describe each element of each river reach. These values can be easily selected in Excel to create a graphic representing the progress of these concentrations along the river.

All the obtained outputs can be readily adapted for use in any geographic information systems software, which is particularly useful since it allows a better interpretation of the results when dealing with real-world situations.



	Start	End	Length	Qm	Diam	MS_Coef	E.Sew
Sew 1	1	7	17720	0	0	100	
Sew 2	2	6	17720	34.7222	355	100	
Sew 3	3	9	13928.4	0	0	100	
Sew 4	4	10	11180.3	5.78704	200	100	
Sew 5	5	10	5000	0	0	100	
Sew 6	6	11	7000	92.5926	500	100	
Sew 7	7	8	10000	0	0	100	
Sew 8	8	4	13928.4	0	0	100	
Sew 9	9	10	10000	0	0	100	
Sew 10	10	15	7000	34.7222	400	100	
Sew 11	11	16	7000	98.3796	560	100	
Sew 12	12	7	7000	0	0	100	
Sew 13	13	18	7000	46.2963	355	100	
Sew 14	14	19	7000	173.611	630	100	630
Sew 15	15	14	10000	150.463	630	100	630
Sew 16	16	21	6000	98.3796	560	100	
Sew 17	17	22	6000	17.3611	250	100	
Sew 18	18	24	14317.8	46.2963	450	100	
Sew 19	19	24	6000	185.185	710	100	710
Sew 20	20	19	10000	0	0	100	
	New Sewers		Existing Sewers				
ci (M€)	8.9		0.0				
ce (k€)	132.9		71.6				
cost (M€)	10.7		1.0				
	New Pump Station			Existing Pump Station			
sewer	4						
ci (k€)	58.5			0.0			
ce (k€)	4.0			0.0			
cost (k€)	112.5			0.0			
	New WWTP				Existing WWTP		
node	21	22			24		
pop.	42500	7500			100000		
ci (M€)	4.0	0.5			0.5		
ce (M€)	0.2	0.0			0.4		
cost (M€)	6.5	1.0			5.9		
	Total						
Ci (M€)	14.010						
Ce (M€)	0.823						
Cost (M€)	25.195						

WTP	QmNode	DOmin	Nmax	Nkjmax	Pmax
25	0	8.73803	5.05856	0.97838	0.0428
24	231.481	7.55532	7.05617	3.01742	0.73453
23	0	7.75915	6.18268	1.88513	0.55459
22	17.3611	7.71124	6.07741	1.62654	0.58655
21	98.3796	7.56884	6.50076	1.84231	0.78953

X	L(mg/l)	DO(mg/l)	Q(m3/s)	CLA	N4	N1	N2	N3	P1	P2
0	2.04869	9	3	0.01	0.8	0.18	0.08	4	0.01	0.01
50	2.04499	8.99805	3	0.01	0.79825	0.18012	0.08002	4.00016	0.00999	0.01001
100	2.0413	8.99611	3	0.00999	0.79651	0.18025	0.08004	4.00032	0.00998	0.01001
150	2.03761	8.99419	3	0.00999	0.79477	0.18037	0.08006	4.00048	0.00998	0.01002
200	2.03393	8.99226	3	0.00999	0.79303	0.18049	0.08008	4.00064	0.00997	0.01003
250	2.03026	8.99035	3	0.00999	0.7913	0.18061	0.0801	4.0008	0.00996	0.01003
300	2.02659	8.98845	3	0.00998	0.78957	0.18073	0.08012	4.00095	0.00995	0.01004
350	2.02293	8.98656	3	0.00998	0.78785	0.18085	0.08014	4.00111	0.00994	0.01004
400	2.01928	8.98467	3	0.00998	0.78613	0.18097	0.08016	4.00127	0.00993	0.01005
450	2.01563	8.9828	3	0.00997	0.78441	0.18109	0.08018	4.00143	0.00993	0.01006
500	2.01199	8.98093	3	0.00997	0.7827	0.18121	0.0802	4.00159	0.00992	0.01006
550	2.00835	8.97908	3	0.00997	0.78099	0.18132	0.08022	4.00175	0.00991	0.01007
600	2.00473	8.97723	3	0.00996	0.77928	0.18144	0.08025	4.00191	0.0099	0.01008
650	2.00111	8.97539	3	0.00996	0.77758	0.18155	0.08027	4.00207	0.00989	0.01008
700	1.99749	8.97356	3	0.00996	0.77588	0.18167	0.08029	4.00223	0.00989	0.01009
750	1.99388	8.97173	3	0.00996	0.77419	0.18178	0.08031	4.00239	0.00988	0.01009
800	1.99028	8.96992	3	0.00995	0.7725	0.18189	0.08033	4.00255	0.00987	0.0101
850	1.98669	8.96811	3	0.00995	0.77081	0.182	0.08035	4.00271	0.00986	0.01011
900	1.9831	8.96632	3	0.00995	0.76913	0.18211	0.08037	4.00287	0.00985	0.01011
950	1.97952	8.96453	3	0.00994	0.76745	0.18222	0.08039	4.00303	0.00985	0.01012
1000	1.97594	8.96275	3	0.00994	0.76577	0.18233	0.08041	4.00319	0.00984	0.01013
1050	1.97237	8.96098	3	0.00994	0.7641	0.18244	0.08044	4.00335	0.00983	0.01013
1100	1.96881	8.95922	3	0.00994	0.76243	0.18255	0.08046	4.00351	0.00982	0.01014
1150	1.96526	8.95746	3	0.00993	0.76077	0.18266	0.08048	4.00367	0.00981	0.01015
1200	1.96171	8.95572	3	0.00993	0.7591	0.18276	0.0805	4.00383	0.00981	0.01015
1250	1.95816	8.95398	3	0.00993	0.75745	0.18287	0.08052	4.00399	0.0098	0.01016
1300	1.95463	8.95225	3	0.00992	0.75579	0.18298	0.08054	4.00415	0.00979	0.01016
1350	1.9511	8.95053	3	0.00992	0.75414	0.18308	0.08057	4.00431	0.00978	0.01017
1400	1.94757	8.94882	3	0.00992	0.7525	0.18318	0.08059	4.00447	0.00977	0.01018
1450	1.94405	8.94711	3	0.00992	0.75085	0.18329	0.08061	4.00463	0.00977	0.01018
1500	1.94054	8.94542	3	0.00991	0.74921	0.18339	0.08063	4.00479	0.00976	0.01019
1550	1.93704	8.94373	3	0.00991	0.74758	0.18349	0.08065	4.00495	0.00975	0.01019
1600	1.93354	8.94205	3	0.00991	0.74594	0.18359	0.08068	4.00511	0.00974	0.0102
1650	1.93005	8.94038	3	0.0099	0.74431	0.18369	0.0807	4.00527	0.00973	0.01021
1700	1.92656	8.93872	3	0.0099	0.74269	0.18379	0.08072	4.00543	0.00973	0.01021
1750	1.92308	8.93706	3	0.0099	0.74107	0.18389	0.08074	4.00559	0.00972	0.01022

Figure 8.7 - Output – Excel Sheets

8.4. OptWastewater: application example

In order to illustrate the type of results that can be obtained by applying *OptWastewater*, the program was used for three examples. The three examples – case 1, case 2, and case 3 - are variations of the example given above and depicted in Figure 8.2. In case 1, the example is considered to have neither existing facilities nor a tributary river, resulting in a single main river with a flow of 4 m3/s. In case 2 the flow of the main river is 3 m3/s and contains the discharge of a tributary stream with a flow of 1 m3/s, resulting in a total flow of 4 m3/s ahead of the intersection. In case 3, in addition to the tributary stream the example also considers the presence of a previously existing system comprising three sewers and one WWTP, and thus it is the same to the example presented in section 8.3.1. The limit concentration for the DO in the main river is set at a minimum of 7.5 mg/l in all three cases.

The results obtained by applying *OptWastewater* to the three cases are presented in Figure 8.8. In terms of the total cost of the solutions, case 3 is the cheapest, 25.195 M€, derived from the exploitation of the existing system. In case 1, with the 4 m3/s flow for the entire length of the main river, the solution does not require any adjustment to guarantee the minimum DO of 7.5 mg/l. But in case 2 the flow in the first reaches of the main river is 3 m^3/s, and the water quality restriction forces a larger discharge upstream of the tributary river intersection where the flow of the main river is greater. Therefore the cost of case 2, 28.630 M€, is higher than that of case 1, 27.725 M€. The solution configurations for the three cases are depicted in Figure 8.8 – left. Apart from the presence of existing facilities in case 3, the solutions are broadly similar, requiring the use of three WWTP. Cases 1 and 2 only differ in the transport of the wastewater from one population center. Figure 8.8 - right shows the DO concentration curves, where, as expected, the minimum DO does not fall below 7.5 in any case: 7.539 mg/l for case 1 and 7.555 mg/l for cases 2 and 3. The improvement of the DO concentration resulting from the flow increment given by the tributary stream is perceptible in the curves of cases 2 and 3. The time taken by the program to solve each case was around 5 minutes.

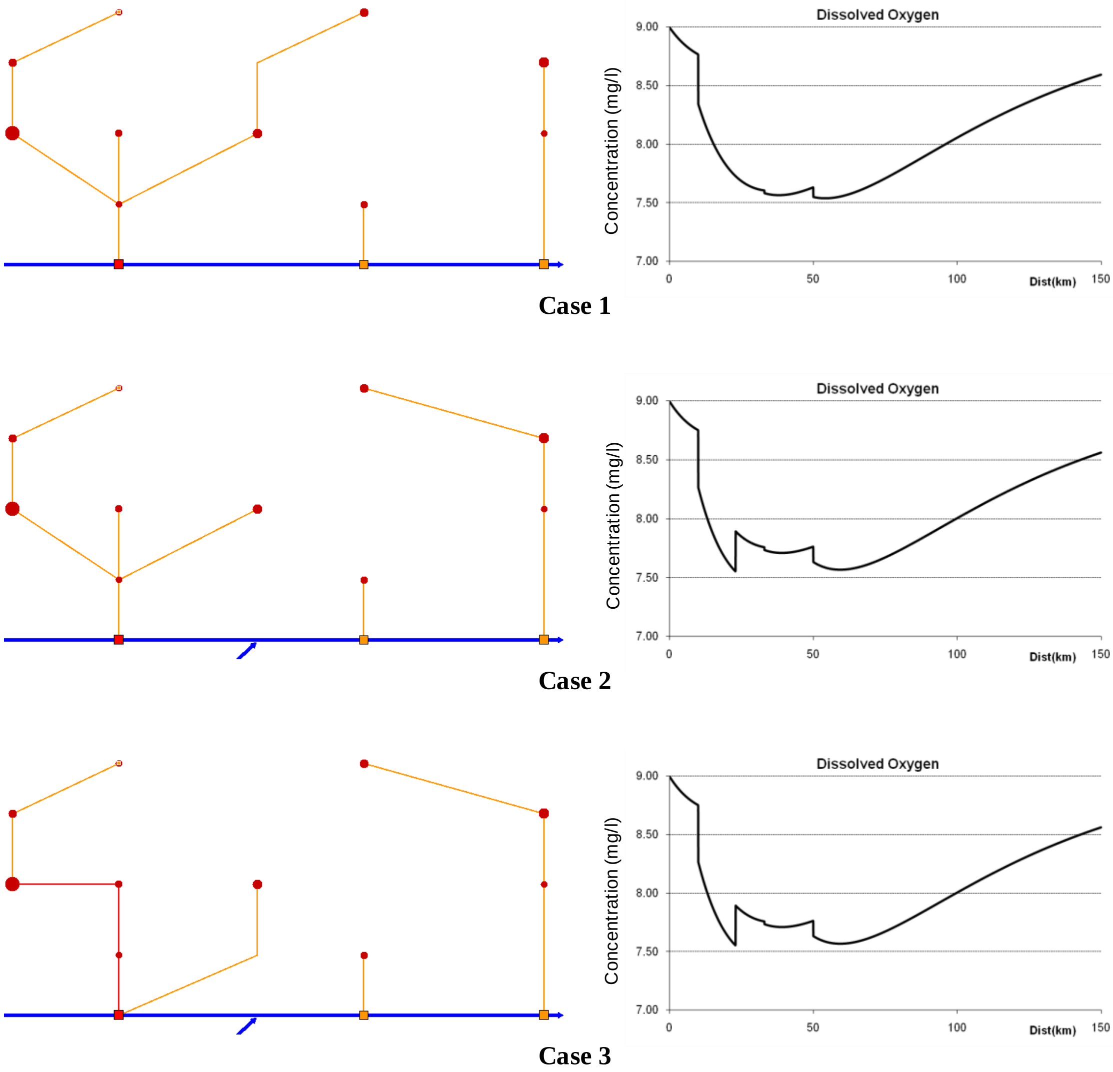


Figure 8.8 - Solutions for the three cases

8.5. Conclusion

OptWastewater, an easy-to-use computer program developed for regional wastewater system planning, has been presented in this chapter. The program is aimed at helping to determine the best possible configuration for the layout of the sewer network, and for the location, type, and size of the pump stations and WWTP to include in the wastewater systems. This is done with the purpose of meeting the quality standards defined for the river, in terms of different water quality parameters: DO, N, Nkj and P. The search for the best regional wastewater system can only be efficient if pursued through optimization models. *OptWastewater* incorporates a variety of optimization models that have recently been developed by the authors: a single-objective optimization model; a multi-objective optimization model; and a robust optimization model. The modular structure of the program allows several analyses involving different conditions to be carried out, and also allows the code to be easily adapted to the needs of future improvements. The nature of the results that can be obtained through the application of *OptWastewater* is illustrated in three examples – case 1, case 2, and case 3. The results obtained through the model demonstrate its potential usefulness in real-world applications.

Chapter 9

Conclusion

This thesis addressed the regional planning of wastewater systems. The collection and treatment of wastewater is essential to guarantee the quality of water bodies and, more generally, the sustainability of water resources. Because of this, and also because wastewater systems are costly and very difficult to reverse, they should be planned efficiently. The main contribution of this thesis is the development of a set of optimization models based on deterministic and robust approaches, aimed at helping planners to find economic and environmentally sustainable solutions for the wastewater generated in a region.

The basic optimization model to tackle wastewater system planning problems at regional level was presented in Chapter 3. The objective of the model is to minimize the costs of a wastewater system to be built in a region, expressing an environmental concern in terms of appropriate water quality parameters in the water body receiving the wastewater discharges. In this initial approach, environmental constraints representing the water quality standards to be guaranteed in a river are considered. The comparison of the results for various combinations of environmental constraints makes clear that the attainment of some water quality standards may have a large impact in solution costs.

The optimization model presented in Chapter 3 relies on a mixed-integer nonlinear formulation, requiring a heuristic method to be solved. A simulated annealing algorithm enhanced with a local improvement procedure is described in detail in Chapter 4 and is used as the solution method for the different models developed during this thesis. Instead of the trial-and-error procedure typically used for the calibration of such algorithm, an optimization approach recurring to a particle swarm algorithm was developed in Chapter 4. This innovative approach is aimed at determining optimum or near-optimum values for the simulated annealing parameters as a function of the geographic and environmental characteristics of the problems to be solved. The results obtained from applying this approach to a large set of test instances clearly indicate that, in general, it will help finding very good quality solutions to real-world planning problems at the expense of reasonable computing effort.

In Chapter 5 the basic optimization model was extended to a multi-objective formulation explicitly taking water quality parameters into account in the objective function. The multi-objective model is handled through the weighting method, which requires decision-makers to express their preferences either in advance or sequentially as they acquire a deeper understanding of the planning problem they are faced with. The results showed the tradeoff between costs and water quality in the receiving water bodies. The multi-objective model presented can be applied to any number of objectives and different water quality parameters.

In the deterministic single-objective and multi-objective optimization models was assumed that parameters were known with certainty. However, infrastructure failures or ill-functioning attributable to the lack of consideration of uncertainty issues in the planning stage is less and less tolerated, and points to the need of investigating robust approaches. In Chapters 6 and 7 different optimization models were presented upon which to base a robust approach to regional wastewater system planning. The models assume that uncertainty can be represented through a set of scenarios with known probabilities. The purpose is to find a wastewater system configuration that, regardless of which scenario occurs, is close to optimal and feasible when cost and water quality goals are considered. In Chapter 6 the uncertainty was considered in the flow of the river receiving the wastewater discharges. Three different robust optimization models were developed corresponding to different ways of capturing uncertainty. A comparison of the results between the models and with results obtained through the model of Chapter 3 was performed. In Chapter 7 the uncertainty derives from the population projected for the region where the system is to be built, corresponding to the future amounts of wastewater produced. For a case study, the population projection was performed using a multiple regression analysis, allowing the generation of a set of different scenarios. The objective of the proposed model is the minimization of the expected regret, defined in terms of overall cost of the solution to be adopted, and subjected to different reliabilities according to the alpha-reliable concept. The results for both robust approaches of Chapters 6 and 7 showed that, with a reasonable cost increase, it is possible to obtain a configuration that is designed to accommodate the set of possible future demands of wastewater collection and treatment. In addition, the allowance of slight infeasibilities in the solution for low probability scenarios can also result in some cost savings. The work described in these chapters explores an important direction of research owing to the technical challenges involved in the shift from a deterministic to a robust approach.

The type of results that can be obtained by the models developed in the course of this thesis is illustrated through several test instances. The partly random rules defined for the generation of test instances was described in Chapter 4 and showed to be an important component of the thesis, to exemplify the application and the potential usefulness of the different models presented. In Chapter 7 the case study applied is based on a real-world situation from a NUTS III region in Portugal. This illustrated the potentialities of the model in a realistic setting, and strengthened the idea that the application to real cases is viable.

A computer program, *OptWastewater*, was developed to incorporate the different optimization models described in this thesis. It was presented in Chapter 8, together with a small example including the consideration of tributaries and previously existing systems. Since *OptWastewater* is a prototype software, it should be subjected to more usability testing and debugging, and can be further improved to fit the needs of planners more accurately. For instance, although the outputs given by the program can be readily adapted for use in any geographic information systems software, this integration may be further developed. As it stands now, *OptWastewater* is a tool already capable of supporting complex decisions.

The applicability of the type of models and approaches presented in this thesis is not affected by the cost functions associated with the infrastructures. However, the calibration of cost functions should be the scope of further work preceding the application to real-world cases. The cost functions employed in the literature commonly rely on sources more than three decades old (US EPA 1981). When using literature data only, accurate estimation of costs can hardly be expected, as cost functions are developed at a given time for a specific region and any extrapolation is not without any risk. Indeed, the early phase of a planning process will require the development of specific cost functions, for instance through statistical analysis using real accounting and market surveys. Different cost functions for each specific problem can be easily replaced in the present decision support tool. One particular application of improved cost functions relates to the expansion of wastewater systems (Ong and Adams 1990). Although previously existent systems have actually been considered during this thesis, through specific cost functions the study of wastewater systems expansion could be further developed.

The approach described in this thesis seems to be particularly suited for developing countries with severe water pollution problems, thus requiring large efforts for the development of wastewater systems. The approach can be used at a macro planning level to define the ideal layout for large regional problems. This is likely to result in a set of local systems, on which further smaller scale planning on the network can be applied in the final stages of design, perhaps based on the same type of approach. The proposed optimization models presented in this thesis can be used separately or as a building block of a large decision support tool designed to cover the various issues involved in the implementation of an integrated water resources management scheme. The models can already be useful to these ends, but there are some topics that deserve further consideration.

The research on the development of robust approaches was substantial, resulting in a variety of models and the assessment of several results. However, some aspects could still be enhanced. A possible direction for future research would be taking into account the uncertainty in other variables, as well as the simultaneous presence of different uncertain variables. Also, it would be interesting to consider new case studies to be applied to the proposed robust approaches. In particular, in the robust optimization models of Chapter 6, different weights might be considered. In this respect, a normalization within the model's formulations could be developed, allowing a better understating of the approach to the decision-maker. With respect to the optimization model of Chapter 7, further research could be done on the development of a new reliability set evaluation method to allow the study of more complex problems, such as with different values for the reliability parameter or improved probability distributions of the scenarios. Other developments in the optimization model of Chapter 7 could be to incorporate explicitly into the model the water quality in the receiving water body, for instance as an objective, or indeed involving a second uncertain variable.

An additional line for future developments can relate to water quality issues. At present the removal efficiencies of the treatment plants are constrained to very high levels in the regulatory environment of most industrialized countries, with small variations (usually between 90% to 100%). Thus, the consideration of different treatment levels in the treatment plants, such as in waste load allocation problems, has little hope of application in the planning of new wastewater systems. But a line of potential improvement arises, for instance, in the expansion of existing systems, by considering the increase of poor treatment levels in plants, either through high removal efficiencies or additional water pollutants removal. Note that the consideration of different wastewater treatment levels in treatment plants corresponds to a new decision variable in the optimization model. Indeed, the model would have to be subjected to some modifications, which could require the development of a new solution method. A possible extension could be the implementation of a dual simulated annealing algorithm (Sahin and Ciric 1998).

The water quality simulation model used during this thesis is steady state (i.e., does not consider temporal variations) and one-dimensional (i.e., represents the water flow and the processes of advection and dispersion in just the downstream direction of the river). Different developments have been made in the field of water quality modeling, resulting in a vast range of models (Cox 2003). An additional line for future developments can be the upgrading of the water quality simulation model. This would increase the complexity of the approach, but enabling it to deal with water bodies such as including lakes, reservoirs, estuaries and coastal waters. Another possible improvement is the consideration of water quality in tributary streams, providing new possible locations for treatment plants discharging effluents into those tributaries. Additionally, non-point sources of pollution could be taken into account, which could also lead to further related research involving the integration of land use planning with wastewater systems (Wang 2001, Cho et al. 2004).

In a different perspective, it should be noted that the knowledge from these studies on wastewater system planning has laid solid foundations for further research addressing other subjects such as wastewater systems management. For instance in sewer rehabilitation planning there are some similarities to the planning approaches presented in this thesis. Optimization models or solutions methods such as those here developed could be adapted and extended to optimize the repair and replacement strategy for a sewer network. Another example relates to real time control of wastewater systems, integrating sewer network, treatment plants, and receiving water (Rauch and Harremoes

1999, Schütze et al. 2004). An approach to real time wastewater systems control can go further to specific devices of the wastewater system, such as pumps, weirs, gates and other particular devices of treatment plants. The real time control central idea is to define, in real-time and in an integrated manner, a more efficient performance to the infrastructure of the system, saving costs while ensuring that the river is not in a critical condition in terms of its water quality parameters. In separate sewage collection systems, real time control can be applied both to treatment plants in several ways and to sewer networks for equalizing loads, reducing sediments or taking action in case of failures. If dealing with combined sewage systems, as it could be required in an expansion of systems that have a component of combined sewage, the most relevant problem relates to overflows. Examples of application of real time control in this case are optimizing overflow volumes or frequencies by, for instance, activating in-line storage, or selecting branches of wastewater overflow according to the respective pollutants levels.

Developments along the lines of research referred above will certainly enhance the proposed approach. Nevertheless, the author believes that this thesis already takes valuable steps toward a regional wastewater system planning. All in all, it provides decision support models that can already be used in real-world decisions that will be extremely helpful for the accomplishment of sustainable development goals.

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