Siting and sizing the components of a regional wastewater system: a multiobjective approach

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Abstract

This paper describes a multiobjective approach for the siting and sizing of the components of a regional wastewater system. This approach can be particularly helpful for the coherent and harmonious implementation of the Water Framework Directive. Three criteria are considered for finding efficient solutions. A simulated annealing algorithm improved by a local search algorithm is used and the results of three case studies are presented and compared.
Keywords: wastewater systems, multiobjective models, simulated annealing.

1 Introduction

The worldwide concern about water and sanitation has been expressed in initiatives like the United Nations Millennium Development Goals. The target to reduce by half the population without sustainable access to safe drinking water and basic sanitation is incorporated in the goal to ensure environmental sustainability. If this target is to be met appropriate wastewater systems have to be implemented. These systems are often designed at a local level. However, better solutions both from the economic and the environmental points of view can be obtained with regional planning.

This work describes a multiobjective approach to regional wastewater system planning. In this type of system, global cost is usually the criterion that is optimized, making it a single-objective problem. The other indicators for achieving a sustainable development are often included as problem constraints, considering some upper and lower limits. However, for some indicators, these limits may be difficult to establish, which can make them easier to handle as criteria. Since the criteria to be optimized are usually incommensurable, it is impossible to find a solution where all these criteria are optimized

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simultaneously, given that the improvement of one results in the deterioration of another. This means that no optimal solution can be found. Still, there are efficient solutions that can be reached, these are non-dominated solutions also known as Pareto solutions.

2 Literature review

The first studies on wastewater system planning were carried out in the 1960s. The great majority of these studies tackle the waste load allocation (WLA) problem, which comprises the determination of the required pollutant removal level at a number of point sources of a stream (Loucks *et al* [15], Katapodes and Piasecki [10]). Another type of wastewater planning problem is the siting and sizing of the different components of a regional wastewater system (Leighton and Shoemaker [13], Tyteca [18]). Improved computational capacities and optimization methods made it possible to solve complex models incorporating all the features occurring in the cost minimization of siting and sizing the different components of a regional wastewater system (Wang and Jamieson [20]). Sousa *et al.* [16] presented a model and the respective computational application to solve this type of problem, called Regional Wastewater Systems Planning (RWSP). The water quality in the receiving stream was taken into account by the introduction of constraints for the maximum wastewater discharge in each treatment plant. In Cunha *et al.* [7], the RWSP model was improved by incorporating a water quality model to allow the determination of water quality parameters after discharge from wastewater treatment plants. This improvement enables the model to guarantee the water quality in the river, besides optimizing the network system design.

Other indicators that could be considered as criteria apart from the minimum cost configuration, particularly for WLA problems, came later: Bishop *et al.* [2] and Lohani and Adulbhan [14] attempted to minimize the deviation of the water quality goals and Tung [17] proposed new indicators in order to optimize four different criteria. These criteria were the maximization of the total waste load allocation, the maximization of the dissolved oxygen (DO) in the stream, the minimization of the equity measure between the various dischargers and the minimization of the major risk of breaching the water quality standards. With the aim of reaching efficient solutions considering the uncertainties, Burn and Lence [4] formulated models for the minimization of different criteria corresponding to a deviation measure of the DO levels. Cardwell and Ellis [5] used a criterion consisting of the number of violations of the DO standards, which was minimized together with the cost of the system. In Lee and Wen [12] the objective of maximization of the assimilative capacity in a multiobjective approach was introduced for the first time. The same work presented a list of previous studies, with the criteria used, and also showing the tendency for change from single-objective to multiobjective approaches. Multiobjective decision analysis under uncertainty has been proposed by Chang *et al.* [6] to solve potential conflicts between safeguarding water quality and economic development. Based on the concept of sustainability, Balkema *et al.* [1] defined three dimensions for multiobjectivity: economic, environmental and socio-cultural. They thus indicated different criteria capable of being optimized, such as energy use, land use, nutrient loss, waste production and social acceptance. Since there are various criteria that can be optimized, a multiobjective approach brought important advantages to the analysis. In water resources problems, Burn and Yulanti [3] were the first to use a genetic algorithm in order to find a Pareto set of solutions in a three-objective problem (the objectives were the balance between the various dischargers, the cost of the system, the water quality in the receiving stream, expressed by the number of standard DO violations). More recently, the non-dominated sorting algorithm II was used by Yandamuri *et al* [21]. Ghosh and Mujumdar [8] used a fuzzy multiobjective model for minimizing the risk in a river water quality management problem. A new global search algorithm developed recently, the Probabilistic Global Search Lausanne, was used to solve the model. Jia and Culver [9] applied a robust genetic algorithm to total maximum daily load allocations.

This paper follows previous work by the authors. It describes a multiobjective approach used to solve the siting and the sizing of the different components of a regional wastewater system. The implementation of this approach makes use of the decision-aid model presented in Cunha *et al.* [7].The simulated annealing algorithm (SA) described in Sousa *et al.* [16] improved by a local search algorithm and including the parameters calibrated by Zeferino *et al.* [22] is used.

3 Multiobjective approach

Multiobjective analysis consists either of the generation of solutions from an infinite number of alternatives, using systematic methods, or of the selection of a solution from a finite set of alternatives, also known as multiattribute analysis, using outranking methods. Since there are an immensurable number of alternatives in wastewater system planning, the solution has to be found by a multiobjective analysis based on the generation of solutions.

Three objectives for planning the wastewater system were established for this study. These objectives match the indicators that usually need to be optimized: the minimization of the capital cost of the system (Ci); the minimization of the operating cost (Ce); and the maximization of dissolved oxygen in the river (DO).

The first indicator is related to the initial investment in the wastewater system, and includes equipment and construction costs. The second concerns the cost incurred during the lifetime of the system, consisting of the recurrent costs of the facilities and the equipment, including energy costs. These operating costs are also related to the initial cost. The last indicator is related to the water quality in the river, measured in dissolved oxygen, since this is one of the most important indicators of water quality.

The approach most often used to solve models with more than one objective is based on the utility theory, turning multiple objective problems into a single objective problem prior to optimization. This is done by means of a weighted summation of the individual objectives. But it would be useful to the decision-maker if there were a set of non-dominated solutions that would allow him to note the trade-offs between the objectives when deciding on a solution. Non-dominated solutions are also called Pareto solutions. This set of solutions represents the frontier with the best solutions that can be achieved. This happens because no enhancements can be found, since the improvement of one objective result in the deterioration of another.

Following the weighted summation approach and considering the objectives previously defined, the objective function will be:

$$\text{Minimize F} = \sum_{i=1}^{3} w_i \times \tilde{f}_i(x_j) \tag{1}$$

where F: aggregate objective function; w_i: weighting values; $\tilde{f}_i(x_j)$: normalized criteria to optimize.

Since the three objectives correspond to different units with variations of different magnitudes, their scores are standardized (2). This standardization makes the objectives dimensionless, while transforming the value of the objective to a proportion contained in the interval between the lowest and highest score.

$$\tilde{f}_i(x) = \frac{f_i(x) - f_i^{min}}{f_i^{max} - f_i^{min}} \tag{2}$$

The weights w_i set the priorities for the decision criteria, indicating the relative importance of each objective. An accurate distribution of weights is one of the bigger challenges in a multiobjective optimization. This usually requires a specific process involving different stakeholders (Lahdelma *et al.* [11]). However, the process of finding the right weights to attribute is not within the scope of this work. The weights must be strictly positive for at least one objective, and have a total sum equal to one.

The single-function F (3) to be minimized is thus expressed by the sum of the weights multiplied by the standardized criteria, giving the following expression:

$$F = W_{Ci} \times \frac{\left(Ci - Ci^{min}\right)}{\left(Ci^{max} - Ci^{min}\right)} + W_{Ce} \times \frac{\left(Ce - Ce^{min}\right)}{\left(Ce^{max} - Ce^{min}\right)} + W_{DO} \times \frac{\left(DO^{max} - DO\right)}{\left(DO^{max} - DO^{min}\right)} \tag{3}$$

where Ci: capital cost; Ce: operating cost; DO: minimum value of the Dissolved Oxygen observed in the river. W_{Ci}, W_{Ce} and W_{DO}: weights.

The variables with superscripts in equation (3) correspond to the maximum and minimum values. The Ci^{min}, Ce^{min} and DO^{max} are obtained from the respective minimization and maximization functions. The other extreme values of these indicators are removed from the worst results obtained for those indicators in the other optimizations.

4 Case studies

The study used three different cases, corresponding to 3 test problems. These problems try to correspond to real-world problems, comprising similar characteristics (Figure 1). They were defined according to rules regarding shape and topography, location and size of population centers, the wastewater generation rate and location and maximum discharge at treatment plants. The implementation method for this can be found in Zeferino *et al* [22]). The three cases selected have different characteristics, in particular concerning the values of the ridges' orientations.

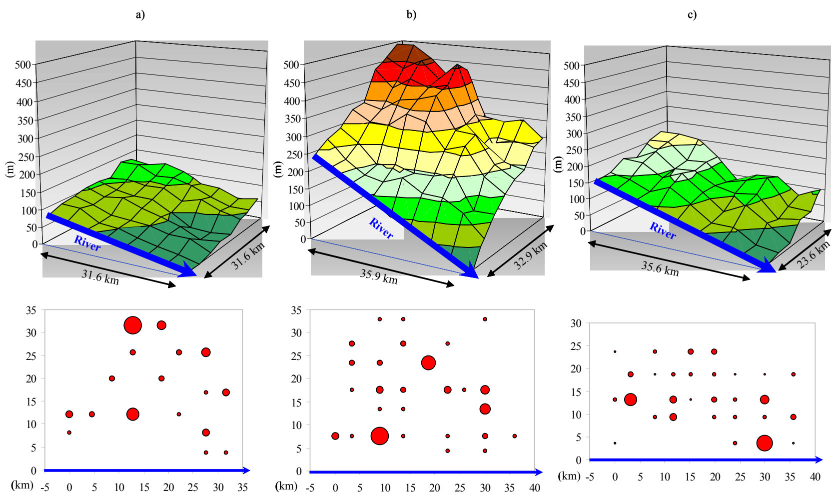

Figure 1: Shape, topography and location of the urban centers of the three regions used for this study.

The first phase of the implementation of the multiobjective approach was to determine the extreme values of the three criteria. This was done using three single objective functions: minimize *Ci*; minimize *Ce*; maximize *DO*. The SA algorithm requires the use of accurate parameters, essential for finding good quality solutions (Sousa *et al.* [16]). For the three cases presented, the four SA parameters (α: sets the initial acceptance rate for candidate solutions with value 10% smaller than the value of the incumbent solution, λ: sets the minimum number of candidate solutions that must be evaluated at each temperature, γ: sets the rate at which the temperature decreases, and σ: sets the maximum number of temperature decreases that may occur without an improvement of the best or the average solution value) were calibrated by the authors in previous work (Zeferino *et al* [22]). They are, for case a): $\alpha = 0.599$, $\lambda = 49$, $\gamma = 0.500$ and $\sigma = 13$; case b): $\alpha = 0.497$, $\lambda = 56$, $\gamma = 0.575$ and $\sigma = 12$; case c): $\alpha = 0.308$, $\lambda = 52$, $\gamma = 0.696$ and $\sigma = 12$. As SA is a random search algorithm, 10 different seeds were used for the pseudo-random generator for each of the three cases. The results obtained are given in Table 1, with *Ci* and *Ce* in M€ and *DO* in mg/l. The results for minimum *Ci* (Ci^{min}), minimum *Ce* (Ce^{min}) and maximum *DO* (DO^{max}) are obtained from each line of each case matrix. Note that all of these values match the diagonal of the matrix. This was expected, since the diagonal corresponds to the values achieved respectively in the minimization and maximization processes. The results for maximum *Ci* (Ci^{max}), maximum *Ce* (Ce^{max}) and minimum *DO* (DO^{min}) are obtained in the same way, and are given by the corresponding maximum or minimum values of each line. The process of defining the proper distribution of weights is not an objective of this work. As mentioned before, different combinations of weights were selected for this study. Once the results for these combinations are obtained, a small set of Pareto solutions is achieved, in order to relate the trade-off between the different criteria. The set of Pareto-optimal solutions makes it possible to see how the solutions change when given different weights. For this study 4 combinations of weights were chosen (Table 2).

Table 1: Results for the extremes.

a)	min Ci	min Ce	max DO
Ci	23,23	24,60	37,63
Ce	0,75	0,73	1,03
OD	6,088	6,108	6,175

b)	min Ci	min Ce	max DO
Ci	29,25	31,57	55,01
Ce	1,20	1,13	1,91
OD	5,800	5,849	5,939

c)	min Ci	min Ce	max DO
Ci	37,16	37,81	56,85
Ce	1,61	1,55	2,00
OD	5,861	5,860	5,923

Table 2: Combinations of weights used.

	W_{Ci}	W_{Ce}	W_{DO}
Combination 1	0,33(3)	0,33(3)	0,33(3)
Combination 2	0,60	0,20	0,20
Combination 3	0,20	0,60	0,20
Combination 4	0,20	0,20	0,60

The solutions generated can also be used to give a set of alternatives that would help with a complementary decision-making aid. This can be done using another multicriteria optimization, based on the selection of a solution from a limited number of alternatives (Vincke [19]). This posterior analysis is not within the scope of this study.

5 Multiobjective results

Once the extremes of each indicator were determined and the different combinations for the weights established, the multiobjective model was solved. This was done for the three cases presented, using 10 different seeds. The parameters used in each case were the same as those employed before in the evaluation of the extreme values. The results for each case are presented in Table 3. The tables on the left correspond to the three cases studied. Each contains the best values of the criteria for each combination. The tables on the right present the results for the respective standardized indicators ($\hat{Ci}$, $\hat{Ce}$ and $D\hat{O}$), where 0% corresponds to the best value of the criteria and 100% to the worst value of the criteria. The extreme values (0% and 100%) were obtained earlier in this work. The summation of these values multiplied by the weight of the respective combination gives the value of the function F that was minimized.

Table 3: Payoff results of the multiple objective problem. Left: Values of the criteria for the three cases; Right: Standardized criteria and F values.

a)	Comb. 1	Comb. 2	Comb. 3	Comb. 4
Ci	26,078	23,670	23,790	26,896
Ce	0,777	0,744	0,739	0,792
DO	6,1697	6,1250	6,1250	6,1744

a)	Comb. 1	Comb. 2	Comb. 3	Comb. 4
Ĉi	19,8%	3,0%	3,9%	25,4%
Ĉe	14,5%	3,6%	2,0%	19,6%
DÔ	6,60%	57,49%	57,49%	1,23%
F	0,136	0,140	0,134	0,098

b)	Comb. 1	Comb. 2	Comb. 3	Comb. 4
Ci	33,265	33,236	33,290	34,956
Ce	1,185	1,186	1,184	1,211
DO	5,9249	5,9249	5,9249	5,9384

b)	Comb. 1	Comb. 2	Comb. 3	Comb. 4
Ĉi	15,6%	15,5%	15,7%	22,1%
Ĉe	7,3%	7,4%	7,2%	10,7%
DÔ	10,29%	10,29%	10,29%	0,61%
F	0,111	0,128	0,095	0,069

c)	Comb. 1	Comb. 2	Comb. 3	Comb. 4
Ci	40,052	40,052	40,402	40,482
Ce	1,576	1,576	1,573	1,590
DO	5,9210	5,9210	5,9210	5,9224

c)	Comb. 1	Comb. 2	Comb. 3	Comb. 4
Ĉi	14,7%	14,7%	16,5%	16,9%
Ĉe	5,8%	5,8%	5,0%	8,8%
DÔ	2,70%	2,70%	2,70%	0,47%
F	0,077	0,105	0,068	0,054

The analysis of the results in each case shows that, once again as expected, the minimum value of the normalized indicators appears in the combination that sets highest weight for the respective indicator.

In relation to the trade-offs between the criteria, the first two indicators, *Ci* and *Ce*, seem to be clearly incommensurable with *DO*. For all the cases studied, the best value of *DO* results in the worst solution for the other indicators. Relating to the indicators *Ci* and *Ce*, the only observation is that it was not possible to find a solution where both were minimized at the same time. Despite the trade-off between these indicators being only slight, this probably means that they are also incommensurable. Regarding the results for F, the minimum value obtained was always in combination 4, that is, when more weight is given to the *DO*. This indicates that it is easier to find solutions where the maximization of the *DO* is near the optimum, thus having suitable values for the other indicators at the same time.

The analysis of how the solutions physically change according to the different combinations of weights is also possible. Figure 2 gives some results of case b), showing the changes that occur in the solutions along with the increase of W_{DO}. The analysis of the three images in Figure 2 clearly shows how the solutions adapt as more weight is given to one criteria, in this case, the maximization of *DO*. In the top left figure, the W_{DO} is only 33.3(3)%, that is, the same as that given to *Ci* and *Ce*. In the top right figure, corresponding to a W_{DO} = 60%, the solution changes through setting one water treatment plant in the first node, in order to improve the *DO* in the river. However, since W_{Ci} = 20% and W_{Ce} = 20%, the solution still considers some aspects for minimizing costs. The figure at the bottom shows a solution where there is no concern with the cost, since it corresponds to the maximization of *DO*. This is equivalent to having a W_{DO} = 100%. As can be seen, the solution is quite unusual, given that it only concerns the wastewater flow that is discharged in each water treatment plant.

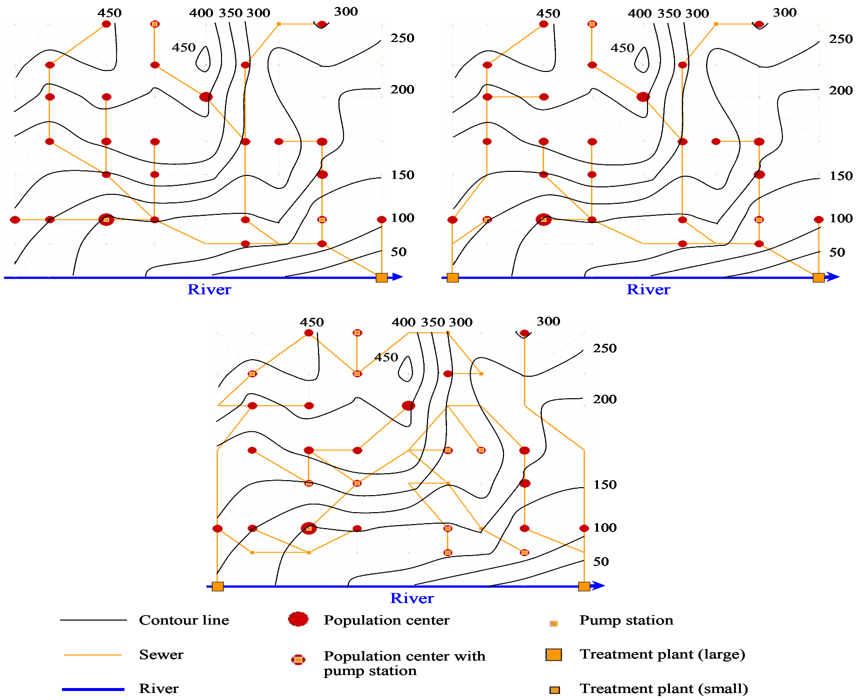

Figure 2: Top left: combination 1; top right: combination 4; bottom: DO maximization.

6 Conclusions

A multiobjective approach has been presented for the siting and sizing of the components of a regional wastewater system. A weighted summation method has been applied to find efficient solutions. The results obtained for three different case studies made it possible to analyse the solutions according to the importance given to each criterion. A set of alternatives was also generated, which helps to support decision-making.

In future work, this multiobjective approach might seek to find a large set of Pareto solutions, showing the best trade-offs between the criteria. More criteria can also be used, to give broader coverage of the objectives involved in regional wastewater system planning.

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