Selection of Evolutionary Multicriteria Strategies: Application in Designing a Regional Water Restoration Management Plan

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Abstract. Sustainability of water resources has become a challenging problem worldwide, as the pollution levels of natural water resources (particularly of rivers) have increased drastically in the last decades. Nowadays, there are many Waste Water Treatment Plant (WWTP) technologies that provide different levels of efficiency in the removal of water pollutants, leading to a great number of combinations of different measures (PoM) or strategies. The management problem, then, involves finding which of these combinations are efficient, regarding the desired objectives (cost and quality). Therefore, decisions affecting water resources require the application of multi-objective optimization techniques which will lead to a set of tradeoff solutions, none of which is better or worse than the others, but, rather, the final decision must be one particular PoM including representative features of the whole set of solutions. Besides, there is not a universally accepted

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standard way to assess the water quality of a river. In order to consider simultaneously all these issues, we present in this work a hydroinformatics management tool, designed to help decision makers with the selection of a PoM that satisfies the WFD objectives. Our approach combines: 1) a Water Quality Model (WQM), devised to simulate the effects of each PoM used to reduce pollution pressures on the hydrologic network; 2) a Multi-Objective Evolutionary Algorithm (MOEA), used to identify efficient tradeoffs between PoMs' costs and water quality; and 3) visualization of the Pareto optimal set, in order to extract knowledge from optimal decisions in a usable form. We have applied our methodology in a real scenario, the inner Catalan watersheds with promising results.

1 Introduction

Water is a precious resource, often jeopardized by its poor quality. Watersheds are constantly subject to increasing threats such as over-exploitation of both surface and ground water, and rising levels of contamination from point and diffuse sources of pollution [8]. In this context, the development and application of new political and management strategies and methodologies, aimed at reversing the degradation in water quantity and quality, has become of vital importance.

Although the European Commission has published a number of guidance documents to ease the implementation of WFD [5-7], no specific methodology has been suggested to evaluate the practical efficiency of PoMs; nor it is mentioned how such combinations of measures should be selected in order to achieve the best cost-effective strategy. In this regard, the restoration of water quality at watershed level (considering the water bodies as management units) is related to a series of objectives that should be taken into account when defining the river basin management plan.

From a methodological point of view, water resources planning and management is a sub-field of natural resource management, in which decisions are particularly amenable to multiple criteria analysis [23]. Moreover, decisions in water management are characterized by multiple objectives and involves several stakeholders groups with different interests and goals. In this regard, decision makers are increasingly looking beyond conventional cost-benefit analysis and looking towards techniques of multi-criteria analysis that can handle a multi-objective decision environment [12].

Water Quality Models (WQM) have been widely used to assess and simulate the efficiency of PoMs in increasing the availability and quality of water. Although such models are useful for evaluating single "what-if" scenarios and testing potential management alternatives, they are unable to solve, in an automatized way, the multi-criteria (cost, water quality, water availability) optimization problems involving the selection of the best cost-effective PoM tradeoffs.

Thus, linear programming [1], non-linear programming [2] and integer programming [25] have been used as alternatives to solve the cost optimization and river quality management model for regional wastewater treatment. Some approaches also consider the river flow as a random variable, building a probabilistic model for it [10]. However, most of the abovementioned approaches, consider only one or two water quality parameters, and, therefore, optimal decisions do not take into account the general state of the watershed regarding its contamination levels, the political strategies and the socioeconomic status of the region. Besides, the inherent nonlinearity of water quality models, the presence of integer decision variables (implementation or not of the WWTPs), and the multiple criteria that are considered simultaneously, make Multi Objective Evolutionary Algorithms (MOEA) a suitable tool to identify tradeoffs between multiple objectives. Over recent years, MOEA [3, 26] have been applied to obtain the Pareto optimal set of solutions for the multiobjective management of watershed with promising results in a single execution [15, 22].

Our proposal to deal with this type of complex problems is a new multicriteria decision support methodological tool, devised to help the decision makers with the management of water quality during WFD implementation at a catchment scale. This methodology results from the integration of various elements: (1) the Qual2k water quality model [16]; (2) a new efficient MOEA, designed to efficiently solve expensive multiobjective optimization problems [24], and a set of tools for visualization and analysis. Our model can incorporate different approaches in order to assess the overall quality of the river, promoting, in this way, new points of view between the stakeholders within the negotiation process, and improving the robustness of the final decision.

Our methodology is being currently used in practice. Specifically, it has been applied on the inner Catalan watersheds to select a robust cost-efficient PoM, in order to achieve the WFD objectives within a reasonable cost. We describe in this paper how to identify the problems on each watershed, how our tool is designed to help in the decision process, and how the optimum PoM is finally selected. We must emphasize that the results provided by our tool have been an essential contribution to the definition of the Catalan hydrological plan to achieve the WFD objectives by 2015. The PoM provided by our model has been recently approved by the Directive Board of the Catalan Water Agency (ACA, by its initials in Spanish). It will be endorsed by the Catalan Government [4], together with the River Basin Management Plan of Catalonia within the next months, being, then, implemented in practice, using, among others, the indications and conclusions obtained by our tool.

2 Multicritera Strategies Selection (MC-SS) Methodology

2.1 The Strategies

The European Directives [5-7] have, as their main motivation, the protection of the environment from the adverse effects of waste water discharges. In order to carry out these directives, the ACA has developed an urban and industrial WWTP program [18, 19], that, in a preliminary study, allowed to identify a number of suitable locations to build more than 670 WWTPs for all the Catalan internal catchments.

Nowadays, there are many reclamation technologies that provide different levels of efficiency in the removal of water pollutants [20]. For the PoM implementation analysis, ACA considered seven WWTP technology types, in terms of their nutrient removal efficiency, and the investment and operational costs, see Table 1. We consider here three different nutrients: ammonium (NH_4), nitrate (NO_3) and phosphates (PO_4). Then, in a hypothetic river with n WWTP possible locations, we would have 7^n different possible combinations of PoMs (strategies). The management solution involves finding which of these PoM combinations are efficient, according to the criteria established by the ACA for the 2010 scenario.

Table 1 Cost and nutrient removal efficiency of the WWTP technologies considered by ACA

Treatment Type	Nutrient Effic. Remov. (%)			Monthly Cost (€/m^3)	
X_T	NH_4	NO_3	PO_4	Investment	Operation
Primary	0	100	0	222 (fixed)	$-0.0001 \cdot Q_P^{0.115}$
Secondary	30	95	50	$2.758 \cdot Q_D^{-0.357}$	$4.645 \cdot Q_P^{0.337}$
Nitrif (60%)	60	10	50	$3.172 \cdot Q_D^{-0.357}$	$5.342 \cdot Q_P^{-0.337}$
Nitrdeni 70%	75	85	50	$3.447 \cdot Q_D^{-0.357}$	$5.342 \cdot Q_P^{-0.337}$
Nitde70% Pr	75	85	75	$3.447 \cdot Q_D^{-0.357}$	$5.574 \cdot Q_P^{-0.337}$
Nitde85% Pre	85	90	80	$4.137 \cdot Q_D^{-0.357}$	$5.574 \cdot Q_P^{-0.337}$
Advanced	95	85	85	$4.413 \cdot Q_D^{-0.357}$	$6.604 \cdot Q_P^{-0.337}$

Here, Q_D and Q_P are, respectively, the design and operational capacities of a WWTP in m^3/day.

2.2 Problem Formulation

Optimization problems with multiple conflicting objectives lead to a set of tradeoff solutions, each of which is no better or worse than the others. Most environmental optimization problems are of this nature. In the WFD scenario, achieving a solution usually implies determining the best tradeoffs strategies in order to satisfy the WFD's objectives within a reasonable cost.

To fix ideas, let us assume that we are dealing with an arbitrary optimization problem with M objectives, all of them to be maximized. Then, a general multi-objective problem can be formulated as follows:

$$\begin{array}{lll} maximize & f_m(x), & m = 1, 2, \dots, M, \\ subject\ to: & g_j(x) \geq 0, & j = 1, 2, \dots, J, \\ & h_k(x) = 0, & k = 1, 2, \dots, K, \\ & x_i^{(L)} \leq x_i \leq x_i^{(U)} & i = 1, 2, \dots, n \end{array} \tag{1}$$

where x is the n-vector of decision variables: $x = (x_1, x_2, \dots, x_n)^T$. In our case, x describes the waste water treatment alternatives, corresponding to each WWTP (strategy) planned to be built in the region. The inequality and equality constraints, $g_j(x), j = 1, \dots, J$, and $h_k(x), k = 1, \dots, K$, together with the bounds $x_i^{(L)}$ and $x_i^{(U)}$, $i = 1, \dots, n$, define the decision variable space D. We say that $f^* = (f_1^*, f_2^*, \dots, f_M^*)$ is a Pareto optimal objective vector if there is no feasible solution x', such that $f' = (f_1', f_2', \dots, f_M') = \big(f_1(x'), f_2(x'), \dots, f_M(x')\big)$, satisfying $f_m^* \leq f_m'$ for each $m = 1, 2, \dots, M$, and $f_j^* < f_j'$ for at least one index j in$1 \leq j \leq M$. Each decision variable $x_i, i = 1, \dots, n$ is actually a discrete variable with 7 possible values, see Table 1. In some cases, and according to the physicochemical characteristics of the stretches, a constraint for the minimum purification treatment must be added.

$$x_i > x_{i,min} \quad \forall i = 1, \dots, n \tag{2}$$

In our specific application to the Catalan inner watersheds, we shall consider two objective functions, the first one having to do with economic factors, the second one dealing with quality aspects of the water.

2.3 The Cost Objective Function

The cost of each strategy corresponds to the sum of the investments in all the catchment WWTP, and the operation costs. The costs for each WWTP facility depend on the flow rate and the type of treatment plant, see Table 1. Then, the first objective function has the form

$$f^1 = \sum_{j=1}^{NumWWTP} \big(ICost_j + OCost_j\big) \tag{3}$$

where j is the WWTP index and $NumWWTP$ is the total number of WWTPs. Besides, $ICost_j = f(Q_D, x_j)$ and $OCost_j = f(Q_P, x_j)$ represent the investment needed to build the j-th WWTP (monthly cost with a 15-year payback period), and the monthly operating costs, respectively.

2.4 The Water Quality Objective Function

The quality criteria considered are the relative concentration of NH_4, NO_3 and PO_4, according to the WFD limits. For a given river stretch, and using the WFD reference, we can evaluate the water quality according to:

$$\delta_s^k = \frac{(WFDL_s^k - AC_s^k)}{WFDL_s^k} \tag{4}$$

where $WFDL_s^k$, AC_s^k and δ_s^k represent, respectively, the WFD concentration limits, the current level of concentration, and the relative concentration of the k-th contaminant (k =2,3,4 stand for NH_4, NO_3 and PO_4, respectively) in the s-th stretch, according to the WFD's limits.

As the global river water quality depends on the quality of all the river stretches, each quality objective function (f^2 is the NH_4 river quality, f^3 is the NO_3 river quality and f^4 is the PO_4 river quality) must be computed based on the values of δ_s^k for all the river sections. There are many possible ways (metrics) to do this [9], possibly leading to significantly different results, but saying that one particular solution is better than the others is a very subjective and subtle issue. To avoid this controversy, it is possible to run our methodology using different metrics, in order to assess the objective functions of global quality of a river with respect to the three contaminants. The three metrics considered are described below:

1. *Utilitarian*

This metric considers all river sections as equivalent, and the objective is, then, to minimize the average of δ_s^k in all river sections. A usual formulation is [17]

$$\min f_u^k = \frac{1}{ns}\sum_{s=1}^{ns} \delta_s^k \quad k = 2,3,4 \tag{5}$$

where *ns* is the number of stretches.

2. *Egalitarian (Smorodinsky-Kalai)*

Another possibility is to seek an equitable strategy that tries to reduce the differences on quality in all river sections. To achieve an egalitarian solution we minimize the Smorondinsky-Kalai objective function [13]

$$\min f_e^k = \mu_k \quad k = 2,3,4 \tag{6}$$

such that

$$\delta_s^k \leq \mu_k \quad k = 2,3,4; \;\; \forall s \in ns \quad \delta_s^k \leq \mu \quad \forall s \in ns$$

3. *Separate Utilities (fulfilling and unfulfilling of WFD)*

This quality function has two different approaches, depending on whether it measures the success or failure in the achievement of a good ecological status. Positive values of the metric mean that the WFD objectives are accomplished for every basin stretch. Otherwise, a negative value means that the WFD objectives are exceeded by at least one river stretch [24].

$$\min f_{su}^k = \begin{cases} \dfrac{1}{ns}\displaystyle\sum_{s=1}^{ns} \delta_s^k & \forall \delta_s^k \geq 0 \\ \dfrac{1}{nsi}\displaystyle\sum_{s=1}^{nsi} \delta_s^k & \forall \delta_s^k < 0 \end{cases} \quad k = 2,3,4 \tag{7}$$

where *nsi* is the number of stretches that do not satisfy the WFD limits

2.5 The MOEA

As we have already mentioned, evolutionary computation methods are becoming increasingly popular for the resolution of environmental problems. Especially suitable are those MOEAs for which conventional techniques are not easily adapted, including nonconvex, mixed integer, non-linear, constrained and/or noisy cost functions. In this regard, a MOEA is a heuristic search algorithm based on a population of strings (called chromosomes) that mimic the process of natural evolution. This population encodes candidate solutions to an optimization problem, called individuals, and evolves toward better solutions.

The MOEA developed in this work to optimize (select) WWTP tradeoff strategies, applies binary gray encoding [11] for each chromosome (optimization string). The length of each optimization string corresponds to a total number of genes, one for each facility. Each gene uses 3 bits to encode the 7 sewage treatment levels for each plant. After decoding the chromosome in treatment levels for each WWTP, the water quality in each stretch is forecasted by the water quality model. The associated goodness-of-fit value is assessed for each one of the cost and quality equations describe above.

The MOEA algorithm applies the usual procedures of selection (tournament), crossover (multi-point) and mutation (uniform) to generate the new population. Efficient convergence is achieved with small populations (10 chromosomes per generation) and mutation rates of 3%. For more details about the convergence of the algorithm see [24]. This MOEA algorithm also introduces elitism by maintaining an external population [3, 26]. In each generation, the new solutions belonging to the internal population are copied to the external population when they are not Pareto-dominated by any solution of this external population. If solutions for the external population are dominated by some of the new solutions, these solutions are deleted from the external population. The external elitist population is simultaneously maintained in order to preserve the best solutions found so far, and to incorporate part of the information in the main population by means of crossover. Elitism is also included in this recombination process, by selecting each of the parents through a fight (tournament) between two randomly-selected chromosomes from the external Pareto set (according to a density criterion), or from the population set (according to their ranking determined through a dominance criterion). The stopping criterion applies when no new non-dominant chromosomes appear in a significant number of generations

2.6 The Water Quality Model

Water Quality Models (WQM) aim at describing the spatial and temporal evolution of the contaminants and constituents characterizing a river flow. Many highly reliable simulation models are available today to evaluate the behaviour of physical systems, such as water bodies, with reasonable computational requirements [21]. In this work, we have used Qual2kw [16], as it represents the state of the art of the last two decades of advances in river water quality modelling and numerical computations.

A range of inputs is used in the water quality simulations, including topography, climate and predicted pressures for 2015, when the objectives of the Water Framework Directives will be effective. Specifically, the main inputs of the WQM are: the head water in all tributaries, point sources (urban, industrial, WWTP; etc), water extractions, diffuse sources of pollution, as well as physicochemical and biological parameters for waste, hydraulics (morphological elements, Manning's roughness coefficient, flow curve, flow). The inflows for the proposed WWTPs are the urban and industrials effluents; based on the information from their discharges in the last 10 years, see [24] for more details.

2.7 *Application of the MC-SS*

Although our methodology has been actually applied to all Catalan internal watersheds, the results presented in this work correspond to its application in the Muga basin. The Muga River has its source in the Eastern Pyrenees, at an approximate height of 1200 meters, flowing towards the Mediterranean Sea, laying its basin entirely within the region of Catalonia, Spain. The Muga River has its headwaters located in mountainous areas, whereas the middle and lower parts of the watershed are subject to Mediterranean climate, implying higher hydrological variability in these last sections. Its main channel has a total length of 64.7 km, draining a watershed of 759 km^2 (2.3% of the total area of Catalonia). It receives an annual average of 177 Hm^3 and its runoff coefficient is 0.285.

In order to apply the Qual2kw model to a river network, the river system must be divided into river elements, having roughly the same hydraulic characteristics. In each cell, the model computes the major interactions between up to 16 state variables and their values for static and dynamic conditions. In this case, the total length of the main channel of the Muga River, and its 12 tributaries is 227 km, which were divided into 54 elements of approximately 5 km length.

For this problem, the ACA considered 41 WWTP locations, each with 7 sewage treatment levels. Each gene uses 3 bits to encode these 7 possible alternatives for the decision variables. Therefore, in the Muga watershed, the number of possible WWTP locations are 41, with a chromosome length of $41 \times 3 = 123$ bits. Then, there are $7^{41} \approx 4.4 \times 10^{34}$ different possible PoM combinations (strategies). The management solution involves finding which of these PoM combinations is efficient according to the ACA estimated conditions for the 2015 scenario, and the goal is to find out which is the most efficient one, according to all the criteria.

The integrated tool (MC-SS) was executed considering simultaneously from 2 to 4 objectives (cost-ammonium-nitrates-phosphates). Runs of the algorithm were performed with different MOEA parameter configuration, using the three quality metrics described above, obtaining, in this way, different Pareto fronts for each one. In order to analyse the convergence process, we consider a MOEA stopping criterion corresponding to a maximum number of WQM evaluations, in this case 10000 evaluations. The number of points obtained for each Pareto front depends on the metric and objectives used.

3 Results

In order to make the proposed methodology useful in the decisions making process, ensuring the achievement of the objectives of the WFD, it is required to work in an efficient manner. In other words, the algorithm must converge close enough to the Pareto solutions in a reasonable number of evaluations of the objective function, making the problem amenable to being solved by low-cost computers. This is especially important in this kind of problems, where the objective function evaluation has a significant computational cost (for some large sized basins, each evaluation may take up to 15 minutes).

The success of our approach was achieved thanks to several improvements on the "standard" multi objective evolutionary techniques, which speeded up the convergence. Specifically, the main improvements in the performance of the algorithm are: (1) the steady state evolution (small population size); and (2) the elitism that allows to reach a good convergence for the Muga basin in less than 6000 evaluations of the WQM, considering simultaneously two objectives. In this regard, a significant increase in the size of the optimization problem only produced a slight increase in the number of evaluations required for our MOEA to reach convergence. On the other hand, an increase in the number of criteria (e.g., from two to four) required more than 10.000 evaluations to achieve convergence. Further improvement on the convergence speed of the MOEA (up to 50%) was achieved by choosing adequate initial strategies from the Pareto fronts obtained in previous executions (e.g., carried out with different metrics or less objectives), rather than generating them in a random way. More details about the convergence process and the configuration of the MOEA parameters can be found on [24].

The use of either water quality metric had little influence on the algorithm convergence. In this regard, we should mention that the egalitarian metric converged slightly faster, because it encompassed a lower number of efficient strategies than the two others, the reason being that only the WWTP located close to those stretches with the worst river quality had influence on the value taken by the egalitarian metric. On the contrary, changes in most of the WWTP had influence in the value taken by the other two metrics (utilitarian and separate utilities). This fact suggests us that one of the main drawbacks of the egalitarian metric is that, by using it, it is difficult to know the general status of the river, because it only informs us about the state of the worst quality stretch.

Once the Pareto frontier is delineated, it must be analyzed. However, special techniques should be used when there are more than two criteria. To accomplish that, we have used Interactive Decision Maps (IDM), see [14], to simultaneously study tradeoffs for up to 7 criteria. The number of efficient strategies provided by the MOEAhen 4 criteria are simultaneously taken into account is quite high, easily exceeding several hundreds. However, by using the IDM, this difficult shape analysis and comparison of simultaneous tradeoffs becomes quite simple. Specifically, the stakeholders performed a preliminary strategy selection, with the IDM visualization tools, and then translated it into the 2D representation. In the 2D diagram, see Figure 1, the *Y* axis represents the cost of the strategies, whereas the *X* axis represents the water quality for each indicator according to (5), (6) or (7). When using separate utilities or egalitarian metrics, the value $X = 0$ corresponds exactly to meeting the WFD objective. The points falling on the left side of the graphs are strategies that do not satisfy WFD goals, and the points on the right side of the graphs do meet them. A positive value indicates good quality in the defined objective. However, applying the utilitarian metric has the inconvenient that it is difficult to know, from the examination of the Pareto frontier, if one specific strategy meets the limits of the WFD, because the value of the stretches of poor quality may be compensated for the value of the stretches of good quality and vice versa.

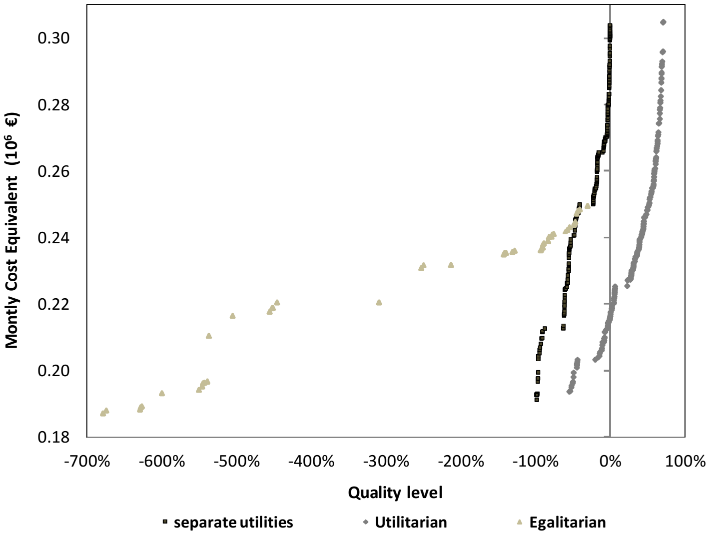

Fig. 1 Pareto fronts based on an optimization using only two objectives (cost and ammonia) for the tree quality metrics (separate utilities, utilitarian, and egalitarian)

The Pareto set is the basic knowledge resource from which the stakeholder will base the decision process, so special care should be taken in order to represent it in an intelligible, yet rigorous, manner. Exploration of the Pareto frontier helps the decision makers to understand the criteria tradeoffs, and to identify, in a direct way, a preferred criterion point.

Additional information can be obtained from the slope of these criteria quality curves (the Pareto front curves). They indicate the sensitivity of the water quality to the water treatment actions, i.e., they provide the cost increase required to achieve a unitary increase on the water quality for each strategy. Figure 1 shows the three Pareto fronts obtained for the same problem with each of the metrics discussed in this paper, considering only the cost and ammonium objectives. As we can observe, the use of one or another metric to calculate the overall river quality has a great influence on the Pareto front shape.

If we analyze Figure 1 in more detail, we see that, for the egalitarian metric, when we increase the budget in most intensive sewage PoMs by 40%, this reduces the WFD ammonium breach in the worst stretch of the river from -700% to -30%. Regarding the separate utilities Pareto metric, a similar increase on the depuration budget of around 50% lead to a drastic improvement on the average quality of those stretches not fulfilling the WFD limits by more than 100%. After such investment, the average river quality was very close to the WFD acceptance limits, and, probably, many of the river sections that, separately, did not satisfy the WFD, now they do. We can also observe that, even for the most intensive sewage PoM, it is impossible to achieve the WFD's objective satisfactorily for the ammonium criteria in this catchment. So, in this case, it would be more reasonable to select a strategy with an associated budget close to 270,000 €/month, because spending more money does not lead to a significant improvement on the water quality results. Finally, if we examine the curve corresponding to the utilitarian metric, we see that positive values are obtained for investments higher than 220,000 €/month. Nevertheless, we must keep in mind that the utilitarian metric only indicates whether the average quality of the river is good or not, but, given a positive overall value, it does not ensure a fulfilment of the WFD in all the stretches.

We have just discussed, the benefits and drawbacks of each metric used, with respect to the visual analysis of the Pareto front. But it is important to note that we must also take into account that the MOEA finds different strategies to be Pareto optimal depending on the metric considered. The utilitarian solution tends to save costs on those WWTP related to river stretches in which depurating is very expensive and *vice versa*, and, then, it weights both contributions. On the contrary, the egalitarian metric will tend to invest almost all the budget on those WWTP highly related to the most contaminated stretches, leaving the rest of the river unaffected. The separate utilities metric partially solves this problem, thanks to the fact that, if there are several stretches violating the WFD's objectives, this metric takes all of them into account (and not only the worst one). Otherwise, when all the stretches fulfill the requirements, this metric is equivalent to the utilitarian one.

In this regard, we must conclude that there is not a perfect metric to help us in the decision making process. Rather, each one can be consider better or worse than the others depending on the (subjective) point of view or the interests of each stakeholder. The main advantage of providing decision makers with different results obtained using various metrics is to reduce, as much as possible, the inherent subjectivity of the decision process. This is achieved by providing the stakeholder with efficient solutions, attained using different metrics to assess the overall quality of river waters and regarding the concentration of each pollutant considered.

By performing a deeper analysis of the decision variables (WWTP) corresponding to all the Pareto optimal solutions obtained for each metric, we can reduce further the subjectivity of the decision process. Specifically, for the basin analyzed in this work, we observe that for 14 of the 41 WWTPs implemented, the treatment level is the same for all the strategies and for any of the fronts obtained. This allows us to fix these 14 values prior to make the final decision, facilitating, in this way, the stakeholders' decision process.

Summarizing, when a final decision is to be found, each stakeholder participates in a decision process that begins by pointing out which regions of the Pareto frontier he or she has specific preferences on. Then, the decision process is followed by the negotiation phase, in which all the stakeholders reach an agreement on some strategies or regions of common interest. Before making the final decision, each of these strategies or regions must be examined in detail.

In this regard, for one selected strategy and pollutant indicator, the use of geographical information systems (GIS) to display, or summarize the information that is automatically generated by our tool might be also of great help.

For a single criterion, it is easier (and more interesting from a stakeholder's point of view) to simultaneously compare results between different strategies, for all months and stretches. In our case, from all the solutions of the Pareto front, we have preselected three strategies (PoM). The first one corresponds to low-intensive and cheap treatments, the second one is related to very intensive treatments (actually, the most expensive ones), and the third one is an intermediate solution between the first two ones. In Figure 2 we have analyzed the monthly results for the three strategies corresponding to the ammonium level at each stretch through a box plot. We can observe how the quality improves as time varies in all stretches but one, fulfilling, in this way, the WFD requirements.

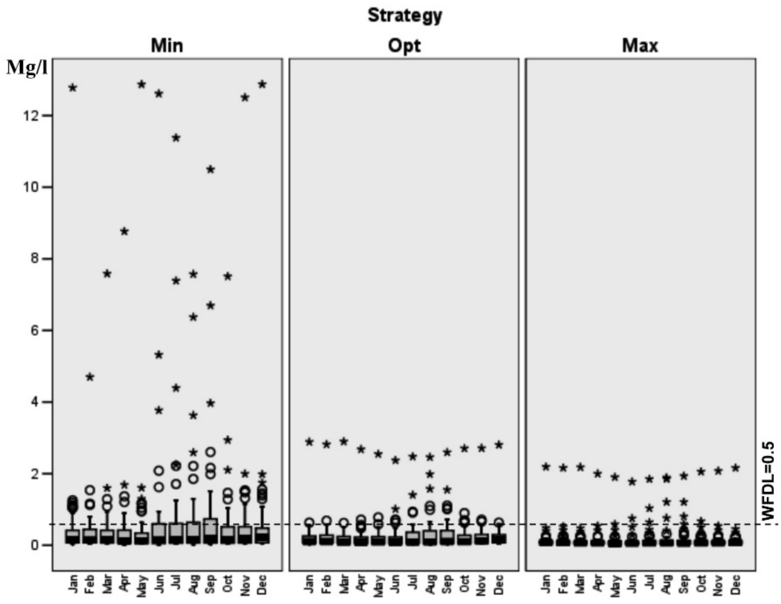

Fig. 2 Box plot for the levels of ammonium in the stretches, depending on the month and the applied purification treatment (Min, Opt, Max) (Ter basin)

4 Summary and Conclusions

A new integrative evolutionary Multi Criteria Strategies Selection (MC-SS) methodology is proposed to help in the selection of the most efficient PoMs for water resources conflicting objectives. It has been applied in the context of the implementation of the WFD in Catalonia. Based on this methodology, a hydroinformatic tool has been developed to assist in the management of water quality at a catchment scale.

The tool is an effective combination of a WQM, which estimates monthly runoff and pollutant loads in the catchments, and the MC-SS algorithm, whose main component is a multicriteria genetic algorithm especially designed and configured to find the Pareto optimal set of PoM (strategies). It is able to incorporate conflicting elements into the analysis, such as environmental objectives and economical issues. Thanks to several improvements on "standard" techniques, which have speeded up the convergence of the MOEA, the approach enables the delineation of non-dominated Pareto optimal solutions in a number of WQM executions that are small enough to be performed on a standard PC, in a timescale that meets the requirements of the Catalan Water Agency (ACA).

We have carried out a case study, taking waste water systems into account, resulting in seven different cleaning technology alternatives, which were also modelled in terms of cost and treatment for each pollutant. Therefore, and in addition to the cost criteria (operating and investment cost), three quality criteria were considered simultaneously: ammonium, nitrate and phosphate. The inherent nonlinearity of the WQM, the integer character of the decision variables (WWTP) and the four criteria simultaneously considered, make MOEA methods more efficient than conventional optimization methods in identifying tradeoffs among multiple objectives.

The selection process of PoMs through which accomplishing the WFD objectives, is a participative process. Then, our methodology has an added value, as it gets suitably integrated within the negotiation and decision processes that the stakeholders must carry out. On the other hand, the stakeholders themselves can suggest new different metrics to assess the global quality of the river water, obtaining new Pareto fronts upon running of the MC-SS. This fact facilitates the stakeholders with a greater degree of intervention on the participation process. Nevertheless, we must keep in mind that there is no perfect metric to help us in the decision making process on the whole basin, although the availability of various fronts obtained from different metrics can be of great help in the decision-making process.

The developed methodology has been shown to be an important tool to: (1) evaluate the effectiveness of the actions that are being currently undertaken to improve water quality; and (2) to provide decision makers with the capacity to explore the multi-objective nature of problems, and to discover tradeoffs amongst objectives avoiding subjectivities as much as possible. We have found this feature to be very helpful, especially during the negotiation process prior to the achievement of the final decision. The main factors intended to guarantee the success on the implementation of the system have been: (1) users' involvement; (2) development of several evolutionary prototypes; and (3) design of a specific user-friendly interface adopted for multicriteria applications and a variety of implemented models and decision support tools.

This tool has been a key factor in the design of part of the PoMs which shall be implemented to achieve the WFD objectives by 2015 in Catalonia. For the Catalan catchments, the model and tools developed have successfully identified the problems in each watershed, for all the WFD criteria considered in this study. Indeed, application of the model has required a reasonably small number of Qual2k executions, keeping the computational time requirements within reasonable limits.

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