Simulation and multicriteria optimization modeling approach for regional water restoration management

**Angel Udías · Roman Efremov · Lorenzo Galbiati ·
Israel Cañamón**

Abstract This paper presents a modeling framework that intends to select the optimal robust wastewater reclamation program of measures (PoM) to achieve the European Water Framework Directive (WFD) objectives in the inner Catalonia watersheds. The integrative methodological tool developed incorporates a water quality model to simulate the effects of the PoM used to reduce pollution pressures on the hydrologic network. A Multi-Objective Evolutionary Algorithm (MOEA) helps to identify efficient trade-offs between PoM cost and water quality. Interactive Decisions Map (IDM)—a multi-criteria visualization—based decision support tool is used to provide a clear idea of the trade-off between water status and the cost to achieve such situation. Lastly, a stochastic simulation model to analyze the sensitivity under varied environmental uncertainties is run. Moreover, the tool is oriented to guide water managers in their decision-making processes. Additionally, this paper analyzes the results of the application of the management tool in the inner Catalan watershed in order to perform the European WFD. This tool has had a key role in the design of part of the PoM which shall be implemented to achieve objectives of the WFD in 2015 in all the Catalan catchments.

Abbreviations
ACA   Catalan Water Agency

A. Udías (✉) · R. Efremov
Dpto. de Estadística e Investigación Operativa, Universidad Rey Juan Carlos, Madrid, Spain
e-mail: angelluis.udias@urjc.es

L. Galbiati
Agència Catalana de l'Aigua, C. Provença 204, Barcelona, Spain
e-mail: galbiati@gencat.cat

I. Cañamón
Dpto. de Matemática Aplicada y Métodos Informáticos, Universidad Politécnica de Madrid, Madrid, Spain

IDM   Interactive Decision Maps
PoM   Program of Measures
WFD   Water Framework Directive
WWTP   Waste Water Treatment Plant
TA   Total Ammonium
TN   Total Nitrogen
TP   Total Phosphorus
TOC   Total Organic Carbon

1 Introduction

Water availability is often jeopardized by the poor quality of this precious resource. 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 (European Commission 2002). In this context, it has become vitally important to develop and apply new political and management strategies and methodologies aimed at reversing this trend in water quantity and quality degradation.

The WFD (European Commission 2000) is the core of the European Union water legislation. It provides the foundation for long-term sustainable water management by taking due account of environmental, economic and social considerations. The main objective of the WFD is to achieve "Good Ecological Status" for all European Water Bodies by the end of 2015. Since the beginning of 2006, European Union Member States have been developing a Program of Measures (PoM), for each water body, in order to reduce current threats and, therefore, achieving Good Ecological Status (WFD's goals) by 2015. Although the European Commission has published a number of guidance documents to ease the implementation of WFD (European Commission 2000, 2001, 2002), no specific methodology has been suggested to evaluate the practical efficiency of PoMs; nor it is mentioned how these combinations of measures should be selected in order to achieve the best cost-effective strategy.

Therefore, EU member states have submitted the river basin management plan, which is a document that defines a strategy to be implemented in order to satisfy the objectives of 2015. 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. It is important to select a cost-effective PoM in order to reduce and, where possible, to eradicate existing and future water deficits, whilst maintaining sustainable economical and social costs.

Water Quality Models are used to quantify and simulate the effectiveness of PoMs in increasing water quality and quantity. Even though water quality models themselves are useful for evaluating single "what-if" scenarios and testing potential management alternatives, they are unable to automatically solve the multi-criteria (cost, water quality, water availability) optimization problems involving the selection of the best cost-effective PoM trade off.

Linear programming (Revelle et al. 1968), non-linear programming (Cai et al. 2001) and integer programming (Bishop and Grenny 1976) have been used to solve the cost optimization river water quality management model for regional wastewater treatment. Some approaches also consider river flow as a random variable constructing a probabilistic water quality management model (Fujiwara et al. 1987). The majority of the mentioned approaches, however, only consider one or two water quality parameters and optimal decisions disregard the general state of the watershed with regard to contamination, political

strategies and the socioeconomical status. The non-linearity of the water quality models, the integer decision variables (waste water treatment plant) and the multiple criteria simultaneously considered make the Multi Objective Evolutionary Algorithms (MOEA) method an interesting option to identify tradeoff among multiple objectives. Over recent years, MOEA (Deb 2001; Zitzler et al. 2003) has been applied to obtain the Pareto optimal set of solutions for watershed management multi-objective problems with very good results in a single execution (Muleta and Nicklow 2005; Ritzel et al. 1994).

Moreover, besides the multicriteria consideration, the WFD implementation is a decision making process related to a negotiation process, which involves several stakeholders with different interests and goals. For this reason, computer procedures for decision screening must be transparent and simple. The Interactive Decision Maps (IDM) visualization technique (Lotov et al. 2004) provides a computer procedure to show in an objective and simple way the solutions defined by the Pareto-optimal trade-off surfaces, helping to avoid any possible subjectivity of the decision makers.

In addition, there exist uncertainties in the inputs of the water quality model (inflow quality and quantity) that may influence the outputs (Benedetti et al. 2010; Haimes 1998). Objective ways of quantifying the relative contribution of those uncertainties should be provided.

In order to overcome these difficulties and assist the management of water quality at catchment scale, this paper describes a new Multi-Criteria watershed restoration decision support tool that has been developed to aid in water management during WFD implementation. This probabilistic framework approach results from integrating the Qual2k (Pelletier and Chapra 2004) water quality model, a MOEA, a stochastic simulation model and graphical analytic tools. It is able to incorporate conflicting elements such as environmental objectives and economical issues into the analysis. It also enables the delineation of non-dominated Pareto optimal set of 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). The tool also caters to situations where correlation between factors influencing two or more alternatives can be used to reduce the uncertainty in the differences between predicted outcomes of alternative actions.

Finally, this paper presents how the management modeling framework and tools developed have been applied in the inner Catalan catchment to select a robust cost-efficient PoM, in order to achieve the WFD objectives within a reasonable cost. It describes how to identify the problems in each watershed, how the tool helps in the decision process and how the optimum PoM is finally selected. In addition, the results of using this methodological tool have made an essential contribution to the definition of the Catalan hydrological plan. The PoM has been recently approved by the board of directors for the Catalan water authority. It will be endorsed by the Catalan government (Diari Oficial de la Generalitat de Catalunya 2010) together with the River Basin Management Plan of Catalonia in the near future. After this phase, the PoM will be implemented in the territory using, among others, the indications and conclusions obtained by the tool described in this paper.

2 Problem stage

The European Directive (European Commission 2000, 2001, 2002) has the goal of protecting the environment from the adverse effects of waste water discharges. In response to this directive, the ACA (Catalan Water Agency) has developed an urban and industrial WWTP program (Diari Oficial de la Generalitat de Catalunya 2003, 2005) that in a preliminary

Table 1 Main characteristics of the inner Catalan river basin ordered from north (*left*) to south (*right*)

	Muga	Fluvia	Ter	Tordera	Besos	Llobregat	Foix	Gaia	Franco
A	863	1008	2989	879	1029	5045	319	429	828
L	67	104	212	59	52	163	45	67	60
P	807	859	828	770	643	675	573	563	575
Q	3.3	9.4	17.1	7.2	6.8	19.3	0.3	0.3	1.1
QCS	13	9	25	14	18	49	5	3	9
WWTP	43	64	131	50	38	217	35	34	56
Strategies	10^{36}	10^{54}	10^{110}	10^{42}	10^{32}	10^{183}	10^{29}	10^{28}	10^{47}
NQE	54	75	370	90	120	540	55	55	95

A: surface (km^2), L: length (km), P: precipitation (mm yr^{-1}); Q: natural average annual inflow (m^3 s^{-1}), QCS: number of quality control stations, WWTP: number of WWTP locations, NQE: number of elements in the Qualk model

Table 2 Cost and nutrient removal efficiency of the WWTP technologies considered by ACA

Treatment type X_T	Nutrient effic. remov. (%)				Monthly cost (€/m^3)	
	ISS	NH$_4$	NO$_3$	P	Investment (15y payback)	Operation
Primary	50	0	0	0	Fix (222)	$-0.0001Q_P^{0.115}$
Secondary	90	30	0	0	$2.758Q_D^{-0.357}$	$4.645Q_P^{0.337}$
Nitrification (60%)	95	60	0	0	$3.172Q_D^{-0.357}$	$5.342Q_P^{-0.337}$
Nitrif.–denitrif. 70%	95	70	70	0	$3.447Q_D^{-0.357}$	$5.342Q_P^{-0.337}$
Nitrif.–denitrif. 70% P removal	95	70	70	100	$3.447Q_D^{-0.357}$	$5.574Q_P^{-0.337}$
Nitrif.–denitrif. 85% P removal	95	85	85	100	$4.137Q_D^{-0.357}$	$5.574Q_P^{-0.337}$
Advanced	100	95	95	100	$4.413Q_D^{-0.357}$	$6.604Q_P^{-0.337}$

Q_D: design capacity of WWTP in (m^3/day), Q_P: operational capacity of WWTP in (m^3/day), ISS: Inorganic Suspended Solids

study, allowed to identify a number of suitable locations to build 38 WWTPs in the Besos catchment and 670 WWTPs (see Table 1) for all the Catalan internal catchments in order to reduce the impact of discharges on all Catalonian surface water bodies.

Nowadays there is a wide variety of reclamation technologies that provide different efficiency levels in the removal of water pollutants (Qasim 1999). For the PoM implementation analysis, ACA considers seven WWTP technology types, which are described in Table 2 in terms of their nutrient removal efficiency and building and operational costs. Then, in one river with a number n of WWTP possible locations, there are 7^n different PoM possible combinations (strategies). The management solution involves finding which of these PoM combinations is efficient according to the ACA estimated conditions for the 2010 scenario.

Water resources planning and management is a sub-field of natural resource management in which decisions are particularly amenable to multiple criteria analysis (Romero and Rehman 1987). Decisions in water management are characterized by multiple objectives and multiple stakeholder groups. Decision makers are increasingly looking beyond conventional cost-benefit analysis and looking towards techniques of multiple criteria analysis that can handle a multi-objective decision environment (Hajkowicz and Collins 2007).

3 Multiple criteria optimization model

For the Catalan basins, the number of possible strategies varies from approximately 10^{28} to 10^{183} (see Table 1). It's not easy to select just a few effective strategies from all those possibilities. Finding the effective PoMs (strategies) is not only difficult due to the large number of possible PoMs, but also because the comparison between two strategies simultaneously depends on cost (investment and operational) and various water quantity and quality criteria: total nitrogen (TN), total ammonia (TA), total phosphorus (TP), and total organic carbon (TOC). All these values are taken into account in the WFD and the solution implies determining the best tradeoff strategies in order to satisfy the WFD's objectives within a reasonable cost.

When a scenario involves an arbitrary optimization problem with M objectives, all of them to be maximized, a general multi-objective problem can be formulated as follows:

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

where x is a vector of n decision variables: $x = (x_1, x_2, \ldots, x_n)^T$. The terms $g_j(x)$ and $h_k(x)$ are called constraint functions and $f_m(x)$ is the multi-objective function. J inequality and K equality constraints are associated with the problem. The last subsets of constraints are called variable bounds, which restrict each decision variable x_i to take a value within an interval with a lower $x_i^{(L)}$ and an upper $x_i^{(U)}$ bound. All of these constraints define the decision variable space D, or simply the decision space. In this case, a Pareto optimal objective vector $f^* = (f_1^*, f_2^*, \ldots, f_M^*)$ is such that it does not exist any feasible solution x', and corresponding objective vector $f' = (f_1', f_2', \ldots, f_M') = (f_1(x'), f_2(x'), \ldots, f_M(x'))$ such that $f_m^* \leq f_m'$ for each $m = 1, 2, \ldots, M$ and $f_j^* < f_j'$ for at least one $1 \leq j \leq M$.

In our case, the vector x describes the waste water treatment alternatives, which correspond to each WWTP (strategy), planned to be constructed in the region.

We use five objectives to reflect the trade-off between minimizing the total annual cost of the implemented WWTP and maximizing the water quality.

$$
F = [f_1, f_2, f_3, f_4, f_5],
\tag{2}
$$

$$
\text{Min} f_1 = \sum_{i=1}^{nm} \left[\sum_{j=1}^{NumWWTP} (ICost_j + OCost_j) \right],
\tag{3}
$$

$$
\text{Max} f_k = WaterQuality_{\text{contaminat } k}
\tag{4}
$$

where:

- k, $2 \leq k \leq 5$: contaminant index
- nm: number of months
- $NumWWTP$: number of total waste water treatment plants.
- $ICost_{Nwwtp} = f(Q_D, X_T)$: is the investment needed to build a WWTP (monthly cost with a 15-year payback period). This cost is a function of the design flow (Q_D) and the type of treatment technology applied (X_T), see Table 2.

- $OCost_{Nwwtp} = f(Q_P, X_T)$: is the monthly operating cost. This cost is a function of the amount of water treated in one month (Q_P) and the type of treatment technology applied (X_T), see Table 2.
- $f_{TA} = WaterQuality_{NH_4}$ is the relative difference between the legal limits and the current concentration of TA in the river water (according to (5)).
- $f_{TN} = WaterQuality_{NO_3}$ is the relative difference between the legal limits and the current concentration of TN in the river water (according to (5)).
- $f_{TP} = WaterQuality_{PO_4}$ is the relative difference between the legal limits and the current concentration of TP in the river water (according to (5)).
- $f_{TOC} = WaterQuality_{TOC}$ is the relative difference between the legal limits and the current concentration of TOC in the river water (according to (5)).

To assess the water quality in a basin over a yearlong period it is necessary to define a quality function (metric), e.g., as shown in (5). This quality function has two different approaches, depending on whether it measures the achievement of the good ecological status or its failure. Positive values of the metric mean that the WFD objectives are reached every month and for every basin stretch. A negative value means that the WFD objectives are exceeded by at least one river stretch during one month.

$$f_k = \begin{cases} \dfrac{\sum_{i=1}^{nm} \sum_{j=1}^{ns} (LDM_{ij}^k - VI_{ij}^k)/LDM_{ij}^k}{nm \cdot ns} & \text{if the WFD levels are satisfied} \\ & \text{for every stretch and month,} \\ \dfrac{\sum_{i=1}^{nmi} \sum_{j=1}^{nsi(i)} (LDM_{ij}^k - VI_{ij}^k)/LDM_{ij}^k}{nm \cdot ns} & \text{otherwise.} \end{cases} \quad (5)$$

where:

- k, $2 \leq k \leq 5$: contaminant index
- ns: number of stretches
- nmi: number of months not meeting the WFD limits.
- $nsi(nmi)$: number of stretches that do not meet the WFD limits. This number is different for each simulation month.
- LDM_{ij}^k: concentration limit of the contaminant k in stretch j and month i, allowed by the WFD's goals.
- VI_{ij}^k: concentration of the contaminant k in stretch j and month i.

Other metrics are possible and have been analyzed (Boon et al. 1997), but we consider that the one described above is more adequate to assess relative fulfillment of the limits imposed by the WFD.

The discrete decision variables, denoted by X_T, are the treatment technologies to be applied at each WWTP. In some cases, a constraint for the minimum wastewater treatment technology could be added. The mathematical formulation of that constraint is the following:

$$X_T > X_{\min} \quad \forall T, \qquad X_T \in \{1, \ldots, 7\}. \quad (6)$$

4 Methodology

The approach proposed in this paper and applied to select the adequate PoM in order to satisfy the WFD in the inner Catalan catchments, combines a water quality model, a mathematical optimization model, Interactive Decision Maps (IDM) (Lotov et al. 2004) and a
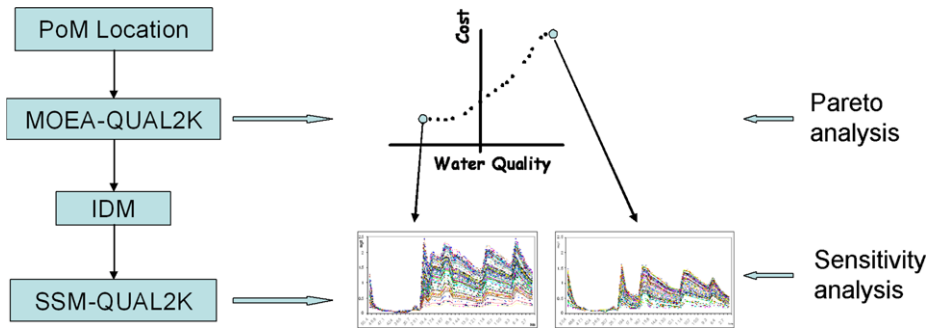
Fig. 1 Scheme of the methodology

stochastic simulation model. Some of these components work integrated, while others are executed sequentially starting from decisions made in previous phases as shown in Fig. 1.

The first step is to define the possible correction measures for each watershed, which consist in a series of proposals (PoM) including the Catalonia urban and industrial WWTP program. This includes deciding which is the most appropriate cleaning technology for each WWTP. The features considered by ACA for each plant type are described in Table 2.

The second step consists in creating economic models to determine the investment (to build a new WWTP) and the operational costs for each plant modality. Both costs depend on the specific technology implemented and the volume of water treated (Table 2). Cost models for the WWTP considered in this study are derived from historical data collected by the ACA over the last 10 years. The total cost of each PoM (strategy) is estimated by summing up the individual costs of each WWTP for each simulated period.

The next step is to build the watershed model according to the "water quality model" (Sect. 4.1 of this paper). All the information related to catchments should be implemented in the Qual2k model. The user's manual (Brown and Barnwell 1987) provides values and ranges for rates and constants, such as O_2 for NH_4 nitrification which a suggested value of 4.57 gO_2/gC, and some values are also available in Bowie et al. (1985). However, Brown and Barnwell (1987) strongly suggest that parameters should be field measured to reduce uncertainty in the model results. Qual2k requires an auto-calibration phase that estimates a series of coefficients which are subsequently used to simulate the present state of the river basin. The resulting characterization provides information related to water resource quantity and quality (Pelletier and Chapra 2004).

The fourth step involves the execution of the MOEA-Qual2k integrated tool which delimitates the Pareto-optimal trade-off surfaces and intends to select the best cost-efficient PoMs (efficient strategies) set. In many multi-objective optimization problems, knowledge about this set helps the decision maker choose the best alternative. One of the main advantages of the proposed modeling framework against other approaches performing an individual cost-effectiveness analysis of each WWTP is the multi-objective simultaneous analysis of the influence of all the WWTP.

Once the Pareto-optimal trade-off surface is delineated, in the fifth step it must be analyzed and decision makers must select some interesting strategies. Special techniques should be used when there are more than two criteria. This is the reason why Interactive Decision Maps (IDM) have been applied, see Muleta and Nicklow (2005), to simultaneously study trade-offs for up to 7 criteria. IDM has been extensively used in water management issues (Lotov et al. 2005; Bourmistrova et al. 2005).

The final decision can't be taken with the unique perspective provided by deterministic scenarios. Water quality and quantity status is subject to uncertainty and varies markedly throughout the year. Reasonable changes in the scenarios exist due to uncertainty in factors such as climate or resource exploitation level and therefore the selected strategies should remain as close as possible to the efficiency level. We should therefore take each of the selected strategies from step 5 and introduce them into the stochastic model integrated with Qual2k in this step.

In the final step, decision makers choose one strategy that shall eventually be conducted in the catchment under study. Decision makers make this final decision comparing the uncertainty analysis results carried out with the previously selected strategies.

4.1 Water quality model

Water Quality Models seek to describe the spatial and temporal evolution of contaminants and constituents characterizing the river flow. Many highly reliable simulation models are available today for estimating the behavior of physical systems such as water bodies, with reasonable computational requirements (Rauch et al. 1998; Shanahan et al. 1998). According to these references, one of the most popular river and stream water quality models is Qual2e (Brown and Barnwell 1987). We chose Qual2k (Pelletier and Chapra 2004) as the water quality model for this application as it is a modernized version of the Qual2e model and is easily embedded with the other tools that integrate the methodology. Qual2k is one-dimensional steady state hydraulics, with non-uniform, simulated steady flow model. For each computational element, a hydrologic balance in terms of flow, a heat balance in terms of temperature, and a mass balance in terms of constituents' concentration are formulated.

The region under study is the one formed by all the internal Catalan watersheds (located in the northeast of Spain) whose main characteristics are described in Table 1. All the rivers in that region flow into the Mediterranean Sea. In this paper we present results for the Besos catchment. The year-averaged daily flow of the Besos main stream outlet is 4.33 m^3/s. The base flow measures from daily streamflow in five stations of the catchment from 2003 to 2006 were obtained from the Catalan Water Agency (available at http://www.gencat.cat/aca).

The main inputs of the water quality model are: the head water in all tributaries, point sources (urban, industrial, WWTP; etc.), water extractions, and diffuse sources of pollution. The inflows for the proposed WWTPs are the urban and industrial effluents. Based on information from urban and industrial discharges over the last 10 years, the evolution of the inflows has been estimated from the relation with the evolution of the population in each city and the evolution of the industrial production. Diffuse pollutants were also considered as input of the Qual2k model. Non-point sources of pollution generated by agriculture activities considerably affect water quality of the Besos River. Measures or estimation about these contributions are not available in Catalonia. In order to set up Qual2k model, information about these sources was provided by the Catalan agricultural department (Udías et al. 2009) and obtained through direct interview with regional and local officers.

In order to apply the Qual2k model to a river network, the river system must be divided in river elements, which have roughly uniform hydraulic characteristics. Within each river cell, the model computes the major interactions between up to 16 state variables and their value for steady state and dynamic conditions. The Besos river main channel, with its 9 tributaries, has 210 km, which were divided into 120 elements with an approximated individual length of 2 km for the simulations.

Twelve Qual2k models must be built for each catchment, one for each month of the year. They all have the same geographical characteristics (geographical longitude and latitude,

time zone, elevation), but each one has different meteorological characteristics (air temperature, dew point temperature, wind speed, cloud cover, shade), as well as physical-chemical and biological parameters for waste hydraulics (morphological elements, Manning roughness coefficient, flow curve, flow).

Before applying the Qual2k, we need to adjust the model parameters to properly represent the actual behavior of the basin. Qual2k includes a general purpose function optimization subroutine based on a genetic algorithm, PIKAIA (Charbonneau and Knapp 1995). This algorithm could automatically calibrate over 120 parameters of the catchment. However, one must consider that when a model has a large number of parameters, excessive computing time is normally needed. To address this problem, before starting the model calibration processes, we perform a standard "one at a time design" on the 120 parameters of the catchment, which varies only one factor from the standard conditions (Daniel 1973) for each simulation. This is done in order to determine which parameters impose the most significant effect on the model performance and therefore which must be the only ones to include in the calibration process. The desired result was to narrow the selection down to 20 parameters that appear to be the most sensitive to the Besos models.

Monthly models were calibrated separately using the monthly data set observed from year 2003 to 2005 at three water quality control stations. Measures of eight water quality parameters are available at each station: dissolved oxygen, suspended solids, biochemical oxygen demand, chemical oxygen demand, ammonium, nitrogen, and total phosphorus. Point source pollutant loads in stream flow were prepared based on data conditions in 2006.

The validation period is based on data conditions in 2006. The Nash-Sutcliffe model efficiency index (Ef) is used to assess the predictive power of hydrological models. For the 2006 simulation, results for the Qual2k model show a value of 0.47 for the Nash-Sutcliffe model efficiency index (Ef) (Nash and Sutcliffe 1970) to assess calibration results obtained for the 12 monthly Besos models. This value is reasonably close to 1 to consider that the model does not introduce important discrepancies for verifying the open decision framework. More details about the water quality models calibration and validation may be found in Udías et al. (2011).

4.2 Multi-Objective Evolutionary Algorithm (MOEA)

The MOEA optimizer is usually capable of mitigating the limitations of standard Multi Criteria Decision Making methods (Udías et al. 2009, 2011), and provides the Pareto cost-efficient PoMs (efficient strategies) set of solutions. In many multi-objective optimization problems, knowledge about this set helps the decision maker to choose the best alternative. The multi-objective analysis of the global influence of all the WWTP is one of the main advantages of the proposed framework over other approaches that make individual cost-effectiveness analyses of each WWTP.

A MOEA is a heuristic search algorithm based in a population of strings (called chromosomes) that mimics the process of natural evolution. This population encodes candidate solutions (called individuals) to an optimization problem and evolves toward better solutions.

The MOEA developed to optimize (select) WWTP trade-off strategies, applies binary gray encoding (Goldberg 1989) 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 reach is forecasted by the Qual2k model. The fitness value for the four quality criteria is assessed by (5) and the cost criteria by (3).

A set of chromosomes makes up a generation. The initial population is generated randomly if no previous basin management information is available. Afterwards, each solution is evaluated according to all the decision-making criteria. At this point, the MOEA selects the solutions that are Pareto dominant from the main population and stores them in the Pareto front population. It also removes the solutions that are dominated by Pareto-optimal trade-off surface solutions (elitism).

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 Udías et al. (2009) and Udías et al. (2011). This MOEA algorithm also introduces elitism by maintaining an external population (Deb 2001; Zitzler et al. 2003). 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 the crossover. Elitism is also included in this recombination process, selecting each of the parents through a fight (tournament) between two randomly-selected chromosomes from the external Pareto-optimal set of solutions (according to a density criterion) or from the population set (according to their ranking determined through a dominance criterion). The stopping criterion is to wait until new non dominant chromosomes don't appear in a significant number of generations.

4.3 Screening stage

As we usually consider more than two criteria, a special technique is used to study the trade-off between them, formed by hundreds of alternatives that the approximation of Pareto-optimal trade-off surfaces determines.

We use IDM that permits the visualization of simultaneous trade-offs for up to 7 criteria, see Lotov et al. (2004). IDM has been previously used in water management issues (Bourmistrova et al. 2002, 2005; Schumann et al. 2006; Fragoso et al. 2010). The information on the Pareto-optimal trade-off surfaces displayed by the IDM technique simplifies the decision makers' choice among the Pareto efficient alternatives. Each stakeholder, familiar with the use of such visualization tools, easily identifies the area of interest (according to his preferences) on a decision map by simply clicking with the computer mouse. This process pre-selects some alternatives in which more accurate analysis involving robustness analysis may be performed. From this pre-selection, we carry out the simulation in order to check if the corresponding strategies (sets of WWTP) are robust decisions, that is, remain efficient under changeable environmental conditions.

This is the fundamental information upon which the stakeholder will base the decision process, so, special care should be taken in order to represent it in intelligible, yet rigorous manner. IDM suits this goal in the framework of participatory decision making (Lotov et al. 2004), when the number of criteria is, at least, five. Here, however, we introduce an example of IDM representing the following three criteria: cost, f_{TA}, f_{TP}, because these criteria represent the most interesting trade-offs for the Llobregat watershed. Figure 2 shows the IDM example that visualizes the Edgewort-Pareto Hull (Lotov et al. 2004), H(Y), for
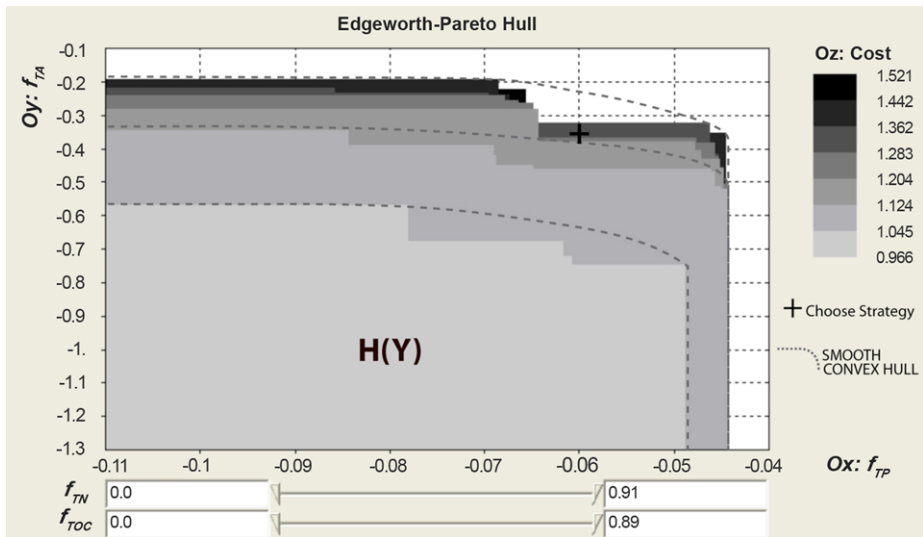
Fig. 2 Example, for the Llobregat catchment, of simple EPH decision map with the corresponding smoothed convex hull

the three above-mentioned criteria. The contaminant criteria are assigned to the axes of the map, whereas the cost criterion is assigned to the grey scale. The total scale of the cost criterion is divided into several half-open intervals of equal length. The slices of H(Y) in the plane of the axis criteria for the values of the third criterion corresponding to the end-points of the intervals are superimposed on a single screen; each slice is represented by a specific color; the legend on the right of Fig. 2 matches the color of each slice to the end point for the interval this slice was computed for. Note that a slice corresponding to a worse value for this criterion encloses the slice corresponding to a better value. This guarantees that non-dominated frontiers for these slices never intersect, even though they might touch. The values for the rest of quality criteria: f_{TN} and f_{TOC}, are set to their lower feasible positions.

In some cases, omitting some data that are irrelevant to the decision-making information may be useful for, mainly, redefining the precise shape of the tradeoff curves between the two quality criteria: f_{TA} and f_{TP}, considering a decision map with "smoothed" tradeoff curves, see Fig. 2. Technically, this is achieved by approximating the convex hull of H(Y), see Lotov et al. (2004). The aim of the removal is to help the decision maker to concentrate on the essential interdependences between the different criteria.

Therefore, exploration of the Pareto-optimal trade-off surfaces by means of the IDM map (Fig. 2) helps to understand the criterion tradeoffs and to identify a preferred criterion point directly at the Pareto trade-off surfaces. Also by means of the Pareto front visualization, e.g., Fig. 2, we can observe that even for the most intensive sewage PoM, it is impossible to satisfactorily achieve the WFD's objective for all the criteria.

Furthermore, the slope of these criteria quality curves (or the Pareto-optimal trade-off surfaces) for each cost level indicates the water quality sensitivity to the water treatment actions. It shows the cost increase required to achieve a unitary water quality improvement for each strategy.

4.4 Stochastic Simulation Model (SSM)

Water quality models are generally deployed to provide insight on source assessments and their impacts on water quality targets as well as the consequences of varied management scenarios (e.g., Parker et al. 2008).

However, the different parameters, such as quantity and quality of waste treatment discharges, irrigation return flows and urban runoff, that characterize regional water quality, are probabilistic in nature. Therefore, the uncertainty is an inherent characteristic in the modeling process (Benedetti et al. 2010).

Stochastic models attempt to mitigate these issues to some degree by representing modeled phenomena as a distribution of possible outcomes. A common implementation is to perturb the input parameter, for example, through the use of Monte Carlo simulations, and assess the likelihood of the different outcomes.

With the information available on each basin, the correlation between different climatic variables, such as precipitation in the nearby measurement stations, variable flows and water quality data is analyzed in order to adequately define the dependencies between them.

As we have, both for water flow and for level of contaminants, the historical series of the river monitoring points placed in the main and the tributaries catchment, we use these collected data to build the cumulative histogram of flow values. These histograms are inverted to generate a random variable for the flow with the observed distribution of the experimental flows. Further an empirical relation between contaminants and flows is determined from the data by regression. So, based in this empirical function, the stochastic simulation model generates the predicted values of the variables at each point of the catchments.

We construct a simulation model in order to govern each of the monthly Qual2k watershed models and in which the type of WWTP is fixed, and execute several thousands times in order to statistically analyze the results for each of the criteria. By running the simulation model tool, it is possible to determine the statistical distribution of each PoM strategy under probabilistic daily environmental and social conditions.

5 Results

After each basin was calibrated and validated, it was integrated into the MOEA, which had previously been developed and tested (Udías et al. 2011). A major difficulty in applying the MOEA methods lies in identifying the appropriate parameter settings to ensure that the decision space of the problem is effectively explored and the entire tradeoff curve is identified. Once this has been set, the MOEA algorithm identifies tradeoffs among multiple objectives in a number of Qual2k executions, ranging from 6,000 to 10,000 depending on the watershed characteristics and the number of WWTP (Udías et al. 2011). This made the problem amenable to being solved by common computers as, even in the larger basins, such the Llobregat [Table 1], each execution of Qual2k requires at most 120 seconds on a computer with an IntelCore2 Duo Processor (2.00 GHz) and 2 GB of RAM Memory.

Considering that 5 criteria (cost, f_{TA}, f_{TN}, f_{TP} and f_{TOC}) are simultaneously under consideration, the number of efficient strategies provided by MOEA is quite high (several hundreds).

Qualitatively, three regions of interest may be identified in the Pareto-optimal trade-off surfaces. In this paper, these regions are named: economic, balanced and environmental. The first is the area where the PoM's are inexpensive and implement purification treatments that are less intense than average. The "environmental region" implements a fairly intensive

Table 3 Example of water quality metric (equation (5)) obtained for the five decision regions selected, ordered from most economical to most expensive, in the Besos basin. Table shows the water quality for each contaminant and the cost (monthly investment + operational cost) for each region

Regions of compromise	Cost (M€/month)	f_{TA}	f_{TN}	f_{TP}	f_{TOC}
Cheapest	0.397	−0.9976	−0.0007	−0.0031	0.8064
Economic	0.528	−0.6018	−0.0007	0.9338	0.8040
Balanced	0.630	−0.3225	0.7956	0.9356	0.8057
Environmental	0.699	−0.2655	0.7938	0.9355	0.8076
Expensive	0.871	−0.2318	0.7983	0.9391	0.8852

purification treatment and is quite expensive, and the "balanced region" would fall in the range between the two other ones.

For example, in the Besos basin, where the MOEA provides a Pareto-optimal set of approximately 500 strategies, Table 3 shows the representative values of these three areas, and two other ones located in the most economical and most expensive regions (all the WWTP are of the "advanced" type). For each one of the five PoM (strategies) preselected, the Qual2k execution provides different outputs for each parameter and river stretch. The quality values shown in Table 1 are the result of these outputs evaluated by means of the metric proposed in (5). Each one of these strategies represents one of the five regions of interest.

While TOC is not affected by investment variations in wastewater treatments, the other quality indicators improve in different rates with the water treatment levels of investments. The average quality of phosphate improves significantly with small investments and, with regard to nitrates; the small breaches in the WFD disappear with intermediate investment. For the f_{TA} the investment produces significant improvements, but fails to achieve the WFD goals, even with the most expensive treatment. The "expensive" alternative region is 24% more expensive than the "environmental" one and 38% more than the "balanced" strategies region, with negligible improvement in f_{TN}, f_{TP} and f_{TOC} and between 13% and 29% in f_{TA}, but it never reaches the WFD goal. The "balanced" strategy regions are, on average, 19% more costly than the "economic" ones, but manage to clearly eliminate the problems of f_{TN} in the basin and reduce the average ammonia concentration 47%.

The next step of the framework, running the stochastic simulation model, is done with the 5 preselected strategies. Figure 3 compares the TA output probability distribution box plot for the 5 strategies that had been previously selected. Note that as the strategies become more intense, improvement is made in the average TA water quality. It is remarkable that the probability distribution becomes less disperse with the intensification of the water treatment, leading to a smaller difference in the water quality between the worst and the best scenarios.

Figure 4 shows the Besos main channel spatial distribution of the TA quality probability distribution for the "balanced" strategy. To get the results shown in this figure, the stochastic simulation model runs the water quality model 600 times. Figure 5 shows the extreme values (95% probability of occurrence) for the five TA spatial statistical distributions, considering the five regions of compromise. In Figs. 4 and 5, the kilometer labeled as km 0 in the x axis corresponds to the confluence with the Mediterranean Sea. There are no significant pollution problems in the first 25 km of river segment. However, for the last 25 km, non compliance of the TA WFD limits is very probable in at least 4 stretches. Similar simulation and statistical analysis process should be repeated for all regions under study and all the criteria.

Fig. 3 Example of the f_{TA} quality metric (equation (5)) statistical distribution for the five previously selected WWTP strategies
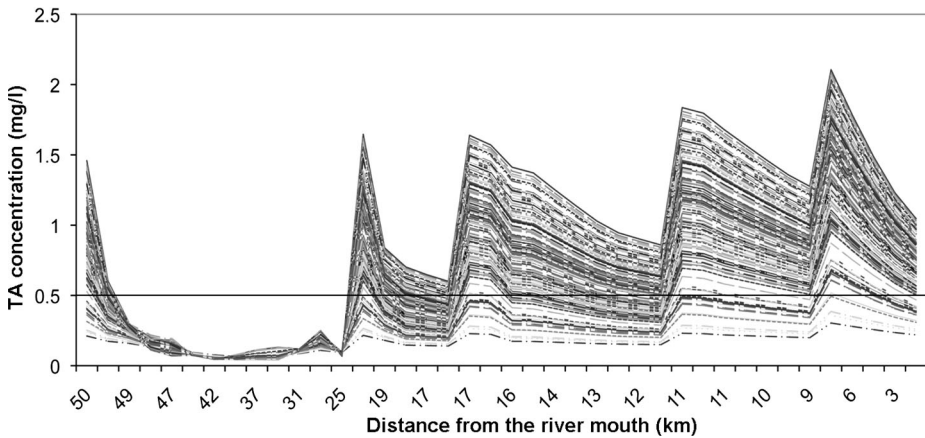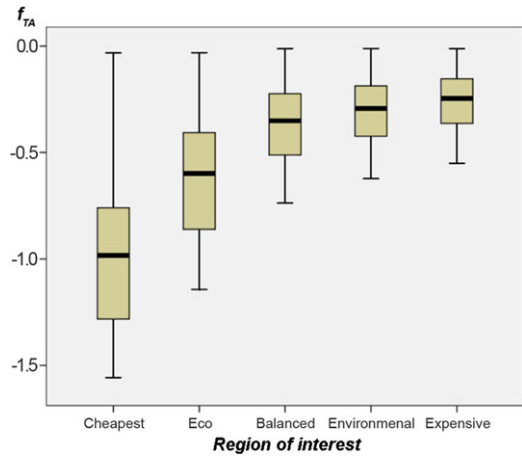

Fig. 4 2D TA concentration statistical distribution along Besos main channel for the balanced strategy. The WFD limit in TA in this stretches is 0.5

The objectives were achieved in all sections in the best possible environmental situation, given that for all sections shown in Figs. 4 and 5 the WFD limit for ammonia is 0.5 mg/l. However, the total compliance is relatively unlikely, as it depends on the level of investment in purification and in the probability that the limits allowed by the WFD be violated, which vary significantly. All these analyses usually help to reach an agreement in a single region of interest in which the PoM shall finally be implemented in.

We also apply the IDM to obtain neighboring strategies for the final region selected in the second step. In Fig. 2, the chosen strategy designated by the black cross seems to be reasonable enough from the point of view of the tradeoff between the pivotal criteria: phosphates and ammonium. The alternatives located near the goal (Fig. 2) are listed on Table 4. These alternatives are either subject to more careful analysis, or can be filtered by another technique, possibly through "eye of the users". Whatever the case, IDM helps to discard most alternatives and to select several ones that do not differ greatly on criteria values with respect to the goal.
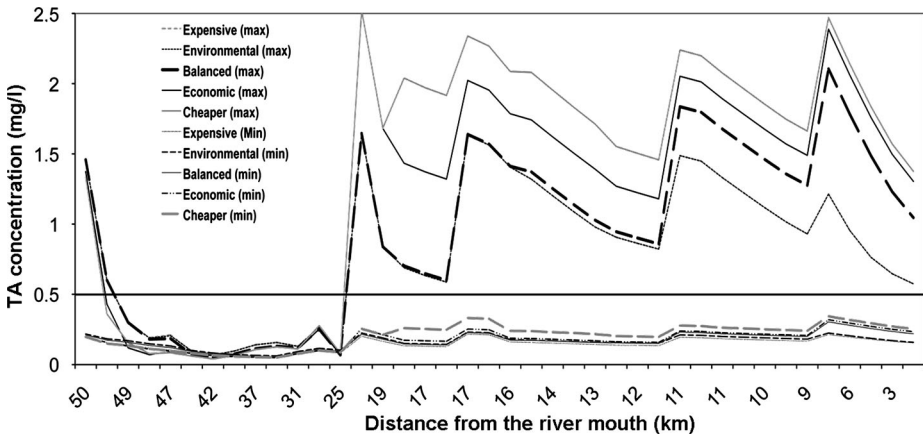
Fig. 5 2D TA concentration statistical extreme probability distribution values along Besos main channel considering the five regions of compromise. (* WWTP location)

Table 4 Example of water quality metric (equation (5)) of six neighboring points (strategies) defined by IDM with respect to the selected strategy in the Llobregat basin (Fig. 2). Table shows the water quality for each contaminant and the cost of the corresponding neighbor strategy

Your aspiration	Cost	f_{TA}	f_{TN}	f_{TP}	f_{TOC}
	1.2	−0.305	0.9	−0.06	0.88
Nearest points					
P1	1.1628	−0.5271	0.8999	−0.0582	0.8768
P2	1.1967	−0.2816	0.9066	−0.0642	0.8857
P3	1.2001	−0.4028	0.9032	−0.0469	0.8766
P4	1.2213	−0.5049	0.8937	−0.0581	0.8781
P5	1.3303	−0.3666	0.9021	−0.0472	0.8789
P6	1.3766	−0.3510	0.9057	−0.0443	0.8790

6 Conclusions

This paper presents an integrative optimization and simulation framework proposed to select the most efficient and robust PoMs in order to reduce both pressure and associated impact in the context of the implementation of the WFD in Catalonia

The methodological tool presented in this paper is an effective combination of a Qual2k model, a MOEA and a screening Pareto-optimal trade-off surfaces tool in a first step, and Qual2k with a stochastic simulation model in a second step. Qual2k model estimates monthly runoff and pollutant loads in the catchments. The MOEA is a multi-criteria genetic algorithm specially designed and configured to find the efficient tradeoff between restoration cost and water quality criteria. The screening tool helps the decision makers to assess local problems in each catchment, and to make initial PoM selections of some deterministic efficient strategies. The stochastic simulation model performs a study of the sensitivity on the previously selected strategies to examine how the catchment behaves under the daily conditions of the variables subject to uncertainty. A range of inputs is used in the water quality simulations, including topography, climate and anthropic pressures predicted for 2015, the

year in which the Water Framework Directive's objectives take effect. Qual2k, integrated with the MOEA, and complemented with the IDM for alternative selection and other user-friendly analysis tools, constitute the main core of the proposed approach.

In this paper, a case study has been carried out by taking wastewater systems into account and considering seven different alternatives for the cleaning technology to be used, also modeled in terms of both cost and treatment for each pollutant. Therefore, in addition to the cost criteria (operating and investment cost), four quality criteria were considered simultaneously: f_{TA}, f_{TN}, f_{TP} and f_{TOC}.

This framework has shown to be adequate in evaluating the effectiveness of the possible remediation actions to improve water quality. It provides decision-makers the opportunity to explore the multi-objective nature of problems, and to discover tradeoffs amongst objectives, enabling them to make decisions and to select among given alternative solutions in order to achieve PoM management outcomes for the future. The model also considers the uncertainties of climate and environmental variables. The main factors intended to guarantee the system implementation success have been: 'early-end users' involvement; development of several evolutionary prototypes; designing 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 designing part of the PoM which shall be implemented to achieve the WFD objectives by 2015. 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.

References

Benedetti, L., De Baets, B., Nopens, I., & Vanrolleghem, P. A. (2010). Multi-criteria analysis of wastewater treatment plant design and control scenarios under uncertainty. Environmental Modelling & Software.

Bishop, A. B., & Grenny, W. J. (1976). Coupled optimization-simulation water quality model. *Journal of the Environmental Engineering Division*, *102*(5), 1071–1086.

Boon, P. J., Holmes, N. T. H., Maitland, P. S., Rowell, T. A., & Davies, J. (1997). A system for evaluating rivers for conservation (SERCON): development, structure and function. In P. J. Boon, & D. L. Howell (Eds.), *Freshwater quality: defining the indefinable?* (pp. 299–326). Edinburg: The Stationery Office.

Bowie, G. L., Mills, W. B., Porcella, D. B., Campbell, C. L., Pagenkopf, J. R., Rupp, G. L., Johnson, K. M., Chan, P. W. H., Gherini, S. A., & Chamberlin, C. E. (1985). Rates, constants, and kinetic formulations in surface water quality modeling. EPA/600/3-85/040, U.S. Environmental Protection Agency, Washington, DC.

Bourmistrova, L. V., Efremov, R. V., & Lotov, A. V. (2002). Decision-making visual support technique and its application in water resources management systems. *Journal of Computer & Systems Sciences International*, *41*(5), 759–769.

Bourmistrova, L. V., Efremov, R. V., Bushenkov, V. A., Buber, A. L., & Brainin, N. A. (2005). Experience of model integration and Pareto frontier visualization in the search for preferable water quality strategies. *Environmental Modelling & Software*, *20*(2), 243–260.

Brown, L. C., & Barnwell, T.O. Jr. (1987). The enhanced stream water quality models, Qual-2E and Qual-2E, UNCAS: Documentation and Users Manual. EPA /600/3-87/007, Envir. Res. Lab., Envir. Protection Agency (EPA), Athens, GA.

Cai, X., McCinney, D. C., & Lasdon, L. S. (2001). Solving nonlinear water management models using a combined genetic algorithm and linear programming approach. *Advances in Water Resources*, *24*(6), 667–676.

Charbonneau, P., & Knapp, B. (1995). *A user's guide to PIKAIA 1.0*. NCAR Technical note 418+IA (Boulder: National Center for Atmospheric Research).

Cho, J. H., Sung, K. S., & Ha, S. R. (2004). A river water quality management model for optimising regional wastewater treatment using a genetic algorithm. *Journal of Environmental Management*, *73*(3), 229–242.

Daniel, C. (1973). One-at-a-time-plants. *Journal of the American Statistical Association*, *68*, 353–360.

Diari Oficial de la Generalitat de Catalunya (DOGC) (2003). Programa de sanejament d'aigües residuals industrials (PSARI-2003). Núm. 3986, 13/10/2003.

Diari Oficial de la Generalitat de Catalunya (DOGC) (2005). Programa de sanejament d'aigües residuals urbanes (PSARU 2005). Núm. 4679, 19.7.2006.

Diari Oficial de la Generalitat de Catalunya (2010). Decret d'aprovació del Pla de gestió del districte de conca fluvial de Catalunya 188/2010, de 23 de novembre. Núm. 5764–26.11.2010.

Deb, K. (2001). *Multi-objective optimization using evolutionary algorithms*. Hoboke: Wiley.

European Commission (2000). Directive 2000/60/EC of the European Parliament and of the Council of 23 October 2000 establishing a framework for Community action in the field of water policy.

European Commission (2001). Strategic document: Common Strategy on the Implementation of the Water Framework Directive.

European Commission (2002). Economics and the environment. The implementation challenge of the Water Framework Directive. Policy summary to the guidance document.

European Commission (2007). Water Framework implementation reports. Towards sustainable water management in the European Union.

Fragoso, R., Bushenkov, V., & Marques, C. (2010). Multi-objective water allocation in the Alqueva region. *Mediterranean Journal of Economics, Agriculture and Environment*, *9*, 28–35.

Fujiwara, O., Gnanendran, S. K., & Ohgaki, S. (1987). Chance constrained model for river water quality management. Jour. Environ. Eng., ASCE.

Goldberg, D. E. (1989). *Genetic algorithms in search, optimization and machine learning*. Reading: Addison-Wesley.

Haimes, Y. Y. (1998). *Risk modeling, assessment, and management, Wiley Series in Systems Engineering*. New York: Wiley.

Hajkowicz, S. A., & Collins, K. (2007). A review of multiple criteria analysis for water resource planning and management. *Water Resources Management*, *21*(2007), 1553–1566.

Lotov, A. V., Bushenkov, V. A., & Kamenev, G. K. (2004). *Applied optimization: Vol. 89. Interactive decision maps, approximation and visualization of Pareto frontier*. Berlin: Springer.

Lotov, A. V., Bourmistrova, L. V., Efremov, R. V., Bushenkov, V. A., Buber, A. L., & Brainin, N. A. (2005). Experience of model integration and Pareto frontier visualization in the search for preferable water quality strategies. *Environmental Modelling & Software*, *20*(2), 243–260.

Muleta, M. K., & Nicklow, J. W. (2005). Decision support for watershed management using evolutionary algorithms. *Journal of Water Resources Planning and Management*, *131*(1), 35–44.

Nash, J. E., & Sutcliffe, J. V. (1970). River flow forecasting through conceptual models part I-A discussion of principles. *Journal of Hydrology*, *10*, 282–290.

Parker, G. T., Drosde, R. L., & Kennedy, K. J. (2008). Modelling the effect of agricultural best management practices on water quality under various climatic scenarios. *Journal of Environmental Engineering and Science*, *7*(1), 9–19.

Pelletier, G., & Chapra, S. (2004). Qual2kw. User Manual (Version 5.1): A modeling framework for simulating river and stream water quality. Washington State Department of Ecology. Olympia, WA.

Qasim, S. R. (1999). *Wastewater treatment plants: planning, design, and operation*. Boca Raton: CRC Press.

Rauch, W., Henze, M., Koncsos, L., Reichert, P., Shanahan, P., Somlyódy, L., & Vanrolleghem, P. (1998). River water quality modeling: I. State of the art. *Water Science and Technology*, *38*(11), 237–244.

Revelle, C., Loucks, D., & Lynn, W. (1968). Linear programming applied to water quality management. *Water Resources Research*, *4*(1), 1–9.

Ritzel, B. J., Eheart, J. W., & Ranjithan, S. (1994). Using genetic algorithms to solve a multiple objective groundwater pollution containment problem. *Water Resources Research*, *30*(5), 1589–1603.

Romero, C., & Rehman, T. (1987). Natural resources management and the use of multiple-criteria decision making techniques: a review. *European Review of Agricultural Economics*, *14*(1), 6–89.

Schumann, A. H., Dietrich, J., & Lotov, A. V. (2006). Workflow oriented participatory decision support for integrated river basin planning. In A. Castelletti & R. Sessa Soncini (Eds.), *Topics on system analysis and integrated water resources management* (pp. 207–222). Amsterdam: Elsevier.

Shanahan, P., Henze, M., Koncsos, L., Rauch, W., Reichert, P., Somlyódy, L., & Vanrolleghem, P., (1998). River water quality modeling: II. Problems of the art. *Water Science and Technology*, *38*(11), 245–252.

Soldevilla, M. V. (2009). Les repercussions de la Directiva Nitrats sobre la filière porcina a Catalunya. Col·lecció Monografies. Generalitat de Catalunya Departament d'Agricultura, Alimentació i Acció Rural.

Udías, A., Galbiati, L., Elorza, F. J., Efremov, R., Gómez, A., Chiang, G., Arrosa, M., & Lejarraga, T. (2009). Algoritmos genéticos para la selección de medidas de restauración de cuencas. In *VI Congreso Español sobre Metaheurísticas, Algoritmos Evolutivos y Bioinspirados (MAEB'09)* (pp. 139–146).

Udías, A., Galbiati, L., Elorza, F. J., Efremov, R., Pons, J., & Borras, G. (2011). Framework for multi-criteria decision management in watershed restoration. *Journal of Hydroinformatics*. doi:10.2166/hydro.2011.107.

Zitzler, E., Thiele, L., Laumanns, M., Fonseca, C. M., & Grunert da Fonseca, V. (2003). Performance assessment of multi-objective optimizers: An analysis and review. *IEEE Transactions on Evolutionary Computation*, *7*(2), 529–533.