Evolutionary network flow models for obtaining operation rules in multi-reservoir water systems

Néstor Lerma, Javier Paredes-Arquiola, Jose-Luis Molina and Joaquín Andreu

ABSTRACT

Obtaining operation rules (OR) for multi-reservoir water systems through optimization and simulation processes has been an intensely studied topic. However, an innovative approach for the integration of two approaches – network flow simulation models and evolutionary multi-objective optimization (EMO) – is proposed for obtaining the operation rules for integrated water resource management (IWRM). This paper demonstrates a methodology based on the coupling of an EMO algorithm (NSGA-II or Non-dominated Sorting Genetic Algorithm) with an existing water resources allocation simulation network flow model (SIMGES). The implementation is made for a real case study, the Mijares River basin (Spain) which is characterized by severe drought events, a very traditional water rights system and its historical implementation of the conjunctive use of surface and ground water. The established operation rules aim to minimize the maximum deficit in the short term without compromising the maximum deficits in the long term. This research proves the utility of the proposed methodology by coupling NSGA-II and SIMGES to find the optimal reservoir operation rules in multi-reservoir water systems.

Key words | agricultural demands, AQUATOOL, decision support system shell, deficits, drought, genetic algorithms, NSGA-II, operating rules, optimization, SIMGES, simulation, water resources system

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INTRODUCTION

Several authors have noted the absence of the application of optimization models to the real management of multi-reservoir water systems (Yeh 1985; Wurbs 1993; Labadie 2004). The applicability of most reservoir operation models is limited because of the 'high degree of abstraction' necessary for the efficient application of optimization techniques (Akter & Simonovic 2004; Moeni *et al.* 2011). On the other hand, other authors such as Oliviera & Loucks (1997) maintain that this is because of institutional limitations rather than technological or mathematical limitations.

Decision-making in environmental and hydrological projects can be complex and inflexible because of the inherent trade-offs among economic, socio-political, environmental and technical factors. The selection of the appropriate management strategies often involves multiple conflicting objectives that should be 'optimized' simultaneously (Makropoulos *et al.* 2008). Thus, there exists the concept of Pareto optimal solutions, i.e. solutions for which it is not possible to improve on the attainment of one objective without making at least one of the others worse. Evolutionary multi-objective optimization (EMO) algorithms offer a means of finding the optimal Pareto front (Farmani *et al.* 2005a; Cisty 2010; Abd-Elhamid & Javadi 2011). The decision-maker can consequently be provided with a set of non-dominated solutions to select a final design solution from that set.

Although the efficiency of these algorithms in solving a number of complicated real-world problems in electrical,

doi: 10.2166/hydro.2013.151

hydraulic, structural or aeronautical engineering has been illustrated (Farmani *et al.* 2005b, 2006, 2007; Hanne & Nickel 2005; Molina-Cristobal *et al.* 2005; Osman *et al.* 2005; Murugan *et al.* 2009), there have been limited applications in the policy analysis of water resources management (Farmani *et al.* 2009; Molina *et al.* 2011). There are recent applications of EMO algorithms related to other water resources research studies, such as the optimal design of water distribution systems or reservoirs (Cisty 2010; Nazif *et al.* 2010; Haghighi *et al.* 2011; Hınçal *et al.* 2011; Louati *et al.* 2011), the conjunctive use of surface water and groundwater (Safavi *et al.* 2010), the control of seawater intrusion in coastal aquifers (Abd-Elhamid & Javadi 2011; Kourakos & Mantoglou 2011; Sedki & Ouazar 2011) or hydrological studies (Dumedah *et al.* 2010; Gorev *et al.* 2011; Hassanzadeh *et al.* 2011).

In this work, an evolutionary multi-objective optimization algorithm, NSGA-II (Non-dominated Sorting Genetic Algorithm; Deb *et al.* 2002), is coupled with the flow network model SIMGES (Andreu *et al.* 1996) and used to assist in the selection of the best operation rules in multi-reservoir water systems.

Despite the development and growing use of optimization models (Labadie 1997), most reservoir planning and operation studies are based on simulation modelling and thus require the intelligent specification of operation rules (OR). Lund & Guzman (1996) review the derived single-purpose operating rules for reservoirs in series and in parallel for different purposes, with the derived rules supported by conceptual or mathematical deduction. Obtaining OR from the results of optimization models can be done using simple (Young 1967) or multiple (Bhaskar & Whitlach 1980) linear regressions and the use of simple statistics, tables and graphs (Lund & Ferreira 1996). Unfortunately, a regression analysis can produce poor results, limiting the use of the obtained OR (Labadie 2004). On the other hand, empirical OR has limited applicability, as for the space rule (Bower *et al.* 1962) or the New York City rule (Clark 1956).

In many real systems, the typical OR is defined by a volume target for a reservoir that had to be maintained. Another typical OR is defined by a curve (variable monthly and constant year by year) for a reservoir or a group of reservoirs that defines a threshold to trigger an action, for example, 'reduce demands' or 'start pumping groundwater'. These types of OR are commonly called Rule Curves (RC), and although they are not always the most efficient rules they are considered the most practical and accepted by users.

This paper aims to show the findings of RC for multi-reservoir water systems by means of the coupling of an EMO (NSGA-II) (Deb *et al.* 2002) with the simulation flow network model SIMGES (Andreu *et al.* 1996). The proposed method is applied to the Mijares River basin water system (Spain) which is characterized by strong drought events, a very traditional water rights system and its historical implementation of the conjunctive use of surface and ground water.

The paper is structured as follows. First, a theoretical background on reservoir operation rules and EMO is developed. A case study is then presented, followed by a description of the integrated methodology in which the implementation of the SIMGES and EMO methods is described. The results are then discussed and several conclusions are drawn.

RESERVOIR OPERATION RULES AND EMO

Traditionally, reservoir operation is based on heuristic procedures, RC and subjective judgments by the operator. This provides general operation strategies for reservoir releases according to the current reservoir level, hydrological conditions, water demands and the time of year (Hakimi-Asiabar *et al.* 2010; Moeni *et al.* 2011). In practice, reservoir operators usually follow RC which stipulate the actions that should be taken depending on the current state of the system (Alcigeimes & Billib 2009). Rule curves, or guide curves, are used to denote the operating rules that define the ideal or target storage levels and provide a mechanism for release rules to be specified as a function of water storage (Mohan & Sivakumar 2007; Hakmi-Asiabar *et al.* 2010). Moreover, RC can be defined as a trigger indicator to start different measures, or actions, for water management.

Obtaining RC from the results given by optimization models by linear regressions is a complex task (Young 1967). Revelle *et al.* (1969) proposed a linear decision rule; Lund & Ferreira (1996) used tables and statistics of the results from an optimization model to obtain the OR of the Missouri River water system. A common technique for obtaining OR and RC is based on an iteration method for river basin simulation models. These iterations are controlled by an optimization algorithm that varies the operation rules depending on the results. For example, Cai *et al.* (2001) described strategies for solving large non-linear water resource management models combining a genetic algorithm (GA) with linear programming (LP), in which a GA/LP approach was applied to a reservoir operation model with hydropower generation and to a long-term dynamic river basin planning model. Simulation models are the most widespread tool for the analysis and planning of water systems. These models are characterized by their flexibility and by the possibility of including very complex elements in the modelling. They allow a more detailed representation of the systems than the optimization models (Loucks & Sigvaldason 1982). River basin management decisions are therefore generally made with the support of simulation models.

Quantitative compromises for the objectives and constraints presented in the methodology section are developed in this study using a multi-objective evolutionary algorithm (MOEA), non-dominated sorting genetic algorithm II (e-NSGA-II) (Deb *et al.* 2002). The concept of Pareto optimality is used to define the multi-objective compromises for a system. A solution is Pareto optimal (or non-dominated) if no other solution in the solution space gives a better value for one objective without also degrading the performance of at least one other objective. MOEAs are heuristic search algorithms that change the approximation to the Pareto optimal set using crossover, selection and mutation operators to mimic natural selection in the populations of organisms in nature. The evolutionary algorithm search process is an iterative process of selection that preserves and reproduces high-quality solutions and that varies to introduce innovation in order to improve the population of solutions.

There are many examples demonstrating that MOEAs can solve complex non-linear and non-convex multi-objective problems (a detailed review is given by Coello-Coello *et al.* 2007). Examples of applications in water resources engineering include groundwater monitoring design (Cieniawski *et al.* 1995; Reed & Minsker 2004; Kollat & Reed 2006), groundwater remediation (Beckford *et al.* 2003; Chan Hilton & Culver 2005; Singh & Minsker 2008) and water resources systems management (Suen & Eheart 2006).

In the last years, there have been new advances and improvements for the NSGA-II MOEA. e-NSGA-II represents an improvement over the original NSGA-II developed by Deb *et al.* (2002) by incorporating epsilon-dominance archiving (Laumanns & Ocenasek 2002) and adaptive population sizing (Harik *et al.* 1997). Epsilon-dominance archiving helps to reduce the computational demand of solving high-dimensional optimization problems (Kollat & Reed 2006) by allowing the user to control the resolution at which the objectives are evaluated and ranked. However, the use of NSGA-II to couple flow network models, which is the application of this research (SIMGES), is a new topic in the literature. The studies on coupling network flow models and EMO algorithms such as NSGA-II are scarce or even non-existent in the literature. The NSGA-II algorithm can be coupled to several other simulation models to provide optimized solutions by taking advantage of the power of those models (Farmani *et al.* 2009; Molina *et al.* 2011).

Most of the OR optimization problems have a multi-objective nature. Consequently, a multi-objective analysis is necessary for identifying the best solutions and simultaneously considering several objectives that are frequently in conflict (trade-offs). Many studies have used multi-objective techniques to address the multi-reservoir optimization problem.

Classical multi-objective approaches such as the weighting approach or the constrain method were used for this purpose (Croley & Rao 1979; Yeh & Becker 1982; Liang *et al.* 1996; Wang *et al.* 2005).

More recent applications use evolutionary multi-objective techniques for the same purpose. Reddy & Kumar (2007) developed a multi-objective differential evolutionary algorithm and applied it to the Hirakud reservoir project (India). Kim *et al.* (2006) applied the NSGA-II algorithm to the Han River basin multi-reservoir system. Chen *et al.* (2007) developed a macro-evolutionary multi-objective genetic algorithm for optimizing the rule curves of a water resources system in Taiwan. Malekmohammadi *et al.* (2011) presented an approach for incorporating flood control and water supply objectives for a cascade system of reservoirs by coupling the NSGA-II algorithm with an ELECTRE-TR1

(Elimination and Choice Translating Reality) postprocessor. Reddy & Kumar (2006) presented a multi-objective evolutionary algorithm to derive operation rules for the multi-purpose Bhadra reservoir system (India). Furthermore, Chang & Chang (2009) applied the NSGA-II algorithm in other reservoir systems in Taiwan to optimize state curves. Lin *et al.* (2008) modified the algorithm SCE-UA (Shuffled Complex Evolution) to use it as a multi-objective tool to determine optimal water policy for the hydroelectric system of Huanren (NE China).

CASE STUDY: MIJARES RIVER BASIN

The Mijares River basin is located in the eastern slope of the Iberian Peninsula (Figure 1). The water system occupies a surface area of 5,466 km^2. The total population of the zone is 363 578 inhabitants, and the urban supply is generated by exploiting pumping wells and the using springs. The total cropped surface is 124 310 ha, of which 43 530 ha (35%) corresponds to irrigated land and the rest (65%) is occupied by dry-land farming. Citruses constitute the predominant crop, with approximately 87% of the irrigated area. The length of the main river branch is approximately 156 km, with an average runoff of 380 $Mm^3\,a^{-1}$.

Two climatologically different geographical areas can be distinguished: a coastal climate with a Mediterranean coastline and a continental climate area located upstream of the Arenós reservoir. The mean annual rainfall of the area is 505 mm, and the average temperature is 14.4 °C according to the Basin Water Plan (CHJ 1998). The maximum altitude is 2,024 m above sea level.

Regarding the storage infrastructure of the basin, there are three main reservoirs: the largest in terms of capacity is the Arenós reservoir (95 Mm^3); located downstream is the Sichar reservoir (49 Mm^3); and finally, located in the tributary Rambla de la Viuda is the María Cristina reservoir (19.7 Mm^3).

The topology of the model for the Mijares water system is shown in Figure 2. The model includes a main course that represents the Mijares River where the Arenós and Sichar reservoirs are located. The other river considered is the tributary Rambla de la Viuda, in which the María Cristina reservoir is located. The different sources of runoff considered are the runoff of the basin upstream of the Arenós reservoir, the runoff from the mid-basin of the Mijares River between the Arenós and Sichar reservoirs and the runoff from the Rambla de la Viuda river flowing to the María Cristina reservoir. The irrigation demand can be grouped into four main zones: traditional, channel 220, channel 100 and María Cristina. The main features of these demands are shown in Table 1. The urban supply comes from the Plana de Castellón aquifer, which is located mainly beneath the coastal plain and is recharged by precipitation, infiltration from irrigation and Mijares riverbed infiltration.

One of the main issues of the basin is the allocation of the resource between the agricultural demands. The traditionally

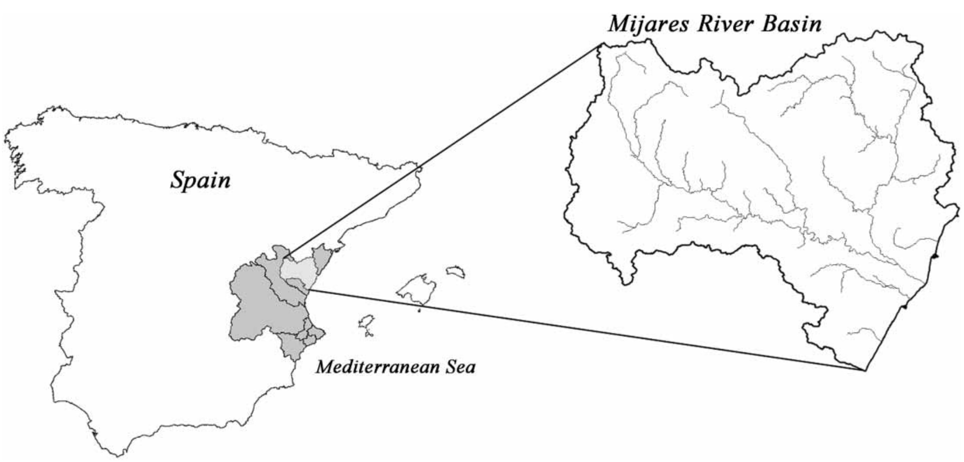

Figure 1 | Location of the Mijares River basin.

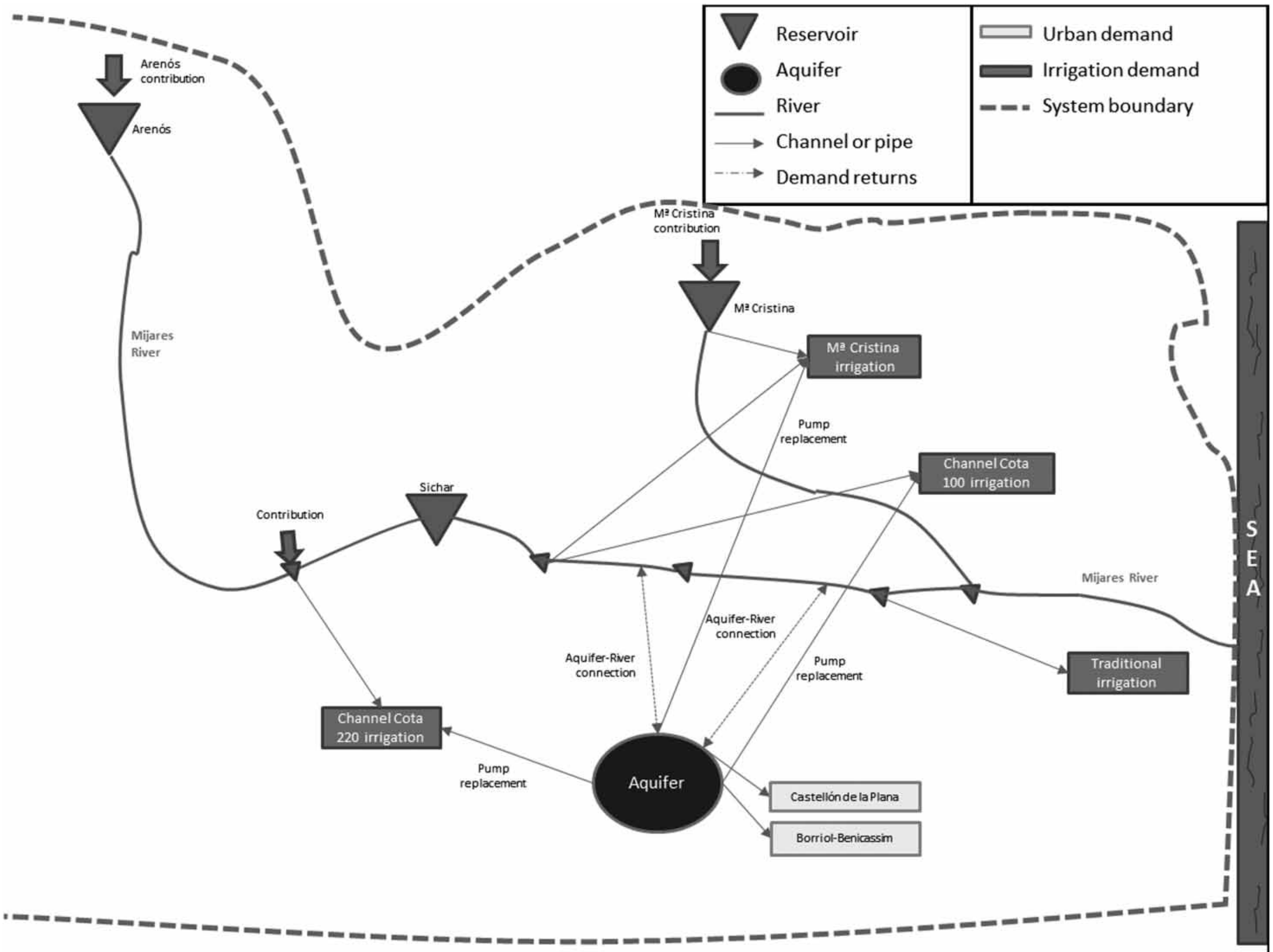

Figure 2 | Topology of the simulation model developed for the Mijares River basin.

Table 1 | Values of the water demand for the irrigated areas of the basin ($Mm^3\ a^{-1}$)

		Mixed irrigated areas		
	Traditional irrigated area	**Channel 100**	**Channel 220**	**María Cristina**
Surface water	65	37	40	25
Groundwater	–			

irrigated area in the low part of the basin is more than a millennium old, so its water rights are predominant over other agricultural uses. On the other hand, the irrigation of the middle part of the basin represents modern irrigation (Channel 220, Channel 100 and María Cristina), also called 'mixed irrigation' because of the possibility of using both surface and ground water. In this situation, it is necessary to establish an OR in order to protect the rights of traditional irrigation over surface water by imposing the use of ground water for modern irrigation. Current management is based on a RC defined in 1970, called Agreement 70 (Figure 3). The indicator of this RC is the storage of the Sichar and Arenós reservoirs. If the sum of the volume of both reservoirs is greater than the defined RC, then all the demands can use

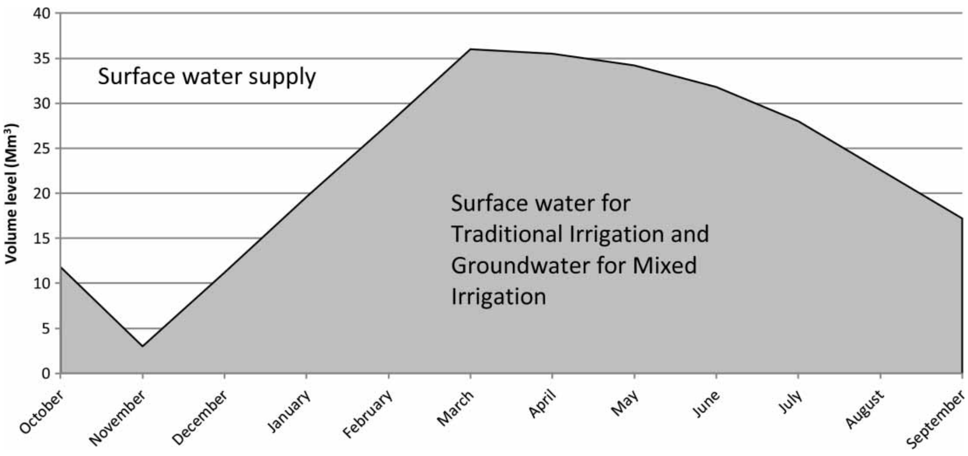

Figure 3 | Rule Curve of 'Agreement 70'.

cheaper surface water. On the other hand, when the volume storage goes down, the RC mixed irrigation demands have to pump water and the remaining surface water is reserved for the traditionally irrigated area.

METHODOLOGY

The methodology estimates the RC for a complex multi-reservoir water system through the iterative use of a river basin simulation model. A popular EMO algorithm that is usually applied in water resources engineering, NSGA-II, has been used. NSGA-II is an EMO algorithm with a specific operator to handle constraints. Furthermore, the simulation of a water basin management model is required. The results obtained by this model represent the situation of the water system under the proposed water management policies. The water basin management model has been developed using the SIMGES module (Andreu *et al.* 1996) included in the decision support system shell (DSSS) AquaTool (Andreu *et al.* 1996). The combination of non-linear algorithms together with linear programming is common in water resources models.

Implementation of the simulation model SIMGES

The method requires multiple iterations of a simulation model that accurately represents the water system. For this purpose, the simulation module SIMGES included in the DSSS AquaTool has been used. SIMGES is based on the conceptualization of river basins by networks comprising arc and nodes. Nodes usually represent the most important elements of the water system, such as divergence and confluence points, reservoirs and demands. On the other hand, arcs represent any water conveyance element (natural or artificial). Furthermore, an internal combination of arcs and nodes within the model allows other types of elements, such as hydroelectric plants and water returns in the internal flow network, to be modelled. Arcs are defined by the initial and final nodes, by the maximum and minimum flows and by the cost that produces each resource unit that flows through it. Mathematically, the simulation model is based on the resolution for each time step (monthly in this case) of an internal conservative flow network.

The equivalent objective function defined in the SIMGES model and simplified for our problem is the following:

$$\begin{aligned}\mathrm{Min}\, F = &\sum_{i=1}^{I}\left(\sum_{n=1}^{m}(V_{n,i,t}(C_n + pn_i)) + (Sp_{i,t}C_{sp})\right)\\ &+\sum_{j=1}^{J} DR_{j,t}(C_{dr} + pn_j) + \sum_{k=1}^{K} DD_{k,t}(C_{DD} + pn_k)\end{aligned} \quad (1)$$

where t is the index for time; i is the index for reservoir; I is the total number of reservoirs in the model; $V_{n,i}$ is the volume of reservoir i in pool n; m is the number of pools in a reservoir; C_n is the cost/benefit of the storage water in pool n; pn_i is the priority number assigned to reservoir i; Sp_i is the spill of reservoir i; C_{sp} is the cost of spills in the reservoirs; DR_j is the deficit of the minimum flow established for river or channel j; C_{dr} is the cost of deficit of a minimum flow; J is the number of rivers and channels; pn_j is the priority number of river j; DD_k is the deficit of demand k; K is the number of demands in the model; C_{DD} is the cost associated with the deficits of the demands; and pn_k is the priority number of demand k.

Restrictions are related to physical constraints or other types of constraints such as legal or environmental constraints. Other constraints such as the balance in each junction or diversion are also taken into account. Figure 4 shows a diagram of SIMGES which takes into account the above aspects and data water system (demands, inflows, etc.) to translate this problem into an internal network flow optimization problem, resolved using the Out-of-Kilter algorithm (Ford & Fulkerson 1962).

The water management within the simulation model is defined in several ways. First, a priority system that sets water demands in order of priority (hierarchical order) is established. Similarly, a hierarchical system is established to define the releases among the reservoirs. Furthermore, the reservoirs are divided into zones such that the model tries to keep all reservoirs in the same zone and starts releasing depending on the priority. Finally, there are operation rules that allow the triggering of decisions based on indicators. These indicators can be the volume stored in one or several reservoirs or the cumulative runoff of several months. The decision can represent the application of a restriction on the demands, expressed as a percentage of one or several demands, on the flow through the turbines, on the ecological flow or on the activation of pumping from the aquifer.

The model developed for the Mijares River basin (Figure 2) represents the current situation of the system quite well. Three runoff inflow elements are considered (one for each reservoir), with historical monthly data obtained from re-naturalized monthly flows for the period 1940–2008. Additionally, the three existing reservoirs have been taken into account (Arenós, Sichar and María Cristina). The demands are considered at the correct aggregation level to represent the different irrigators. Six demands have been considered in the model: two urban demands (Castellón de la Plana and Borriol-Benicassim) and the four above-mentioned agricultural demands. SIMGES allows the surface–groundwater interaction to be modelled in a very complete way with several types of aquifers and river reaches connected to the aquifers. There are requirements for the ecological flows established in several parts of the basin. Within the model, the flows are considered in two specific river reaches with a constant flow of 0.5 $m^3\ s^{-1}$ (1.3 Mm^3/month).

NSGA-II implementation

NSGA-II (Deb et al. 2002) (elitist non-dominated sorting genetic algorithm) is an EMO algorithm with a specific operator to handle constraints. In this method, a fast non-dominated sorting approach with a selection operator is used to create a mating pool by combining the parent and offspring populations and selecting the best solutions with

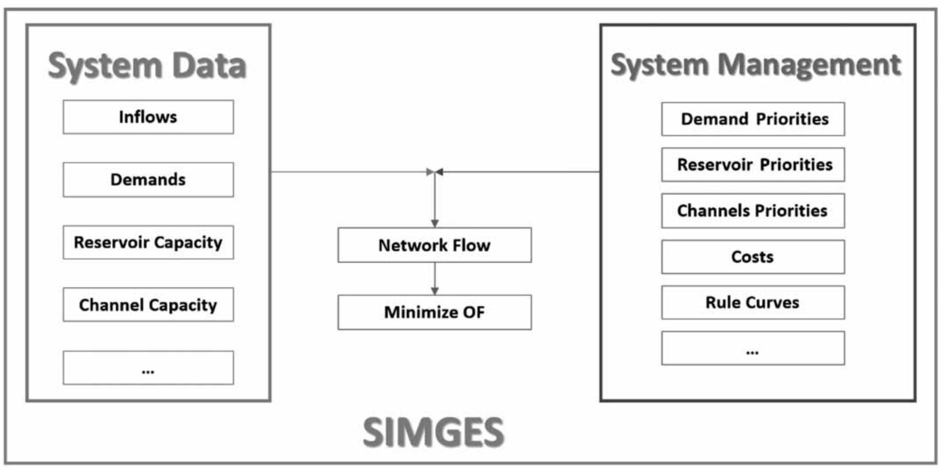

Figure 4 | Flowchart of SIMGES; interaction between data and management system.

respect to the fitness and the spread (Deb *et al.* 2002; Dumedah *et al.* 2010). The next generation is populated starting with the best non-dominated front and progresses through the rest of the fronts until the population size is reached; if in the final stage there are more individuals in the non-dominated front than there is available space, a crowded distance-based niching strategy is used to choose which individuals of that front are entered into the next population. The crowding distance value of a solution provides an estimate of the density of solutions surrounding that solution (Raquel & Naval 2005). In this research, NSGA-II is used for the evaluation of the objective functions that allow the aptitude of the operation rules to be known.

Through this algorithm, the descendant population Q_t (size N) is created using the parent population P_t (size N). Both populations are combined to form R_t with a size of $2N$. By means of non-dominated sorting, the population R_t is classified in different Pareto fronts. Although this process requires more effort, it is necessary because dominance testing between the parent and descendant populations is developed. Once the sorting process is complete, the new population is generated from the configurations of the non-dominated Pareto fronts. This new population is first built with the best non-dominated Pareto front (F_1). The process continues with the solutions from the second front (F_2), the third front (F_3) and so on. Because the population R_t has a size of $2N$ and there are only N configurations that form the descendant population, not all of the front configurations belonging to the R_t population will be placed in the new population. Those fronts that cannot be placed are ignored.

When the last front is under consideration, the solutions that belong to this front can exceed future solutions to be placed in the descendant population (Figure 5). In this case, it is useful to use strategies that allow those configurations to be selected at a scarcely populated area that is far away from the other solutions. This will fill up the rest of the positions of the descendant population instead of choosing configurations randomly.

These strategies are irrelevant for the first-generational cycles of the algorithm because there are many fronts that persist to the next generation. However, as the process moves forward, several configurations become part of the first generation and this front may have more than N genes or individuals. It is therefore important that the non-rejected configurations are chosen through a methodology that guarantees diversity. When the population as a whole converges to the Pareto front, the algorithm ensures that the solutions are separated from each other.

Initially, a parent population P_0 is created in the NSGA-II algorithm (randomly or by an initialization technique). The population is sorted according to the non-dominance of the different levels (sorting of Pareto fronts F_1, F_2, …). For each solution, a flair function is assigned according to its dominance level (1 for the best level), which decreases throughout the process. Sorting by tournament (using a

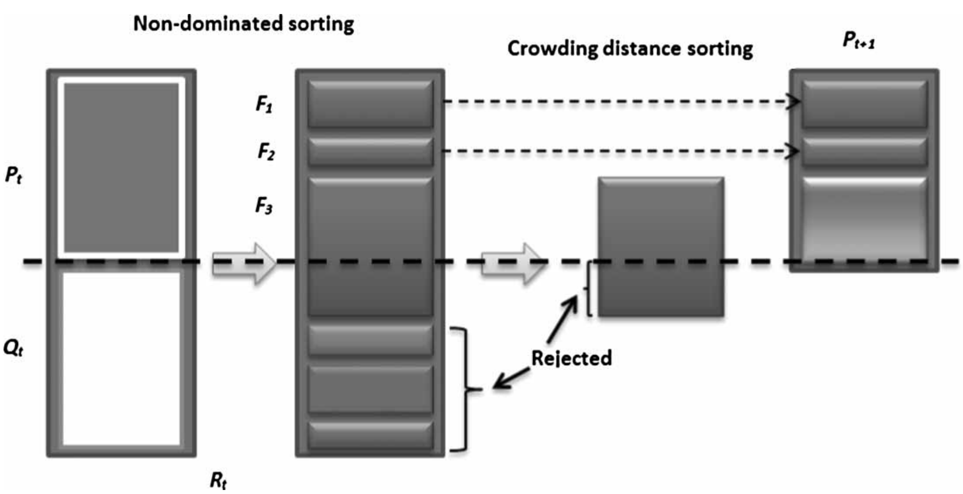

Figure 5 | Schematic diagram of the mechanism for promoting individuals of NSGA-II.

crowding tournament operator), crossing and mutation are used to create the population of descendants Q_0 with a size N. The main phases followed by NSGA-II are:

1. Combine parents and descendants to create $R_t = P_t \cup Q_t$. Develop the non-dominated sorting to R_t and identify fronts F_i, $i = 1, 2 \ldots$, etc.
2. Make $P_{t+1} = \emptyset$, and $i = 1$. While $|P_{t+1}| + |F_i| < N$, make $|P_{t+1}| = |P_{t+1}| \cup |F_i|$ and $i = i + 1$.
3. Sort by crowding ($F_i' < C$, described below) and including at P_i the N–$|P_{t+1}|$ most widespread solutions using the crowding distance values associated with the front F_i.
4. Creating the descendant population Q_{i+1} from P_{i+1} using selection by crowding tournament, crossing and mutation.

Coupling of methods: the multi-objective optimization model

NSGA-II is used to define and test RC for the water allocation model developed with SIMGES. Each individual is composed of 13 values representing the value of the RC in each month of the year (12) and the restriction coefficient (1). The indicator of this RC is the storage of the Sichar and Arenós reservoirs. This RC is imposed in the water allocation model, and a run is performed. The results of this run are used to estimate the objective functions, defined by Equations (2)–(4). The value of this objective function is translated to the multi-objective algorithm to define the aptitude of the RC proposed.

NSGA-II (Deb et al. 2002) is used to examine the SIMGES model and inspect it for inconsistencies or errors and to generate optimal trade-offs between conflicting objectives considering alternative management scenarios simultaneously. Consistency checks can help provide some confidence in the representation of the decision-maker's preferences. In checking for consistency, it is important to detect errors in the decision-making utility function. For utility functions implying a complex preference structure, there is a greater need and opportunity for meaningful consistency checks (Castelletti & Soncini-Sessa 2007).

Attempting to achieve the multiple goals simultaneously requires identifying a compromise in the Pareto optimality. EMO algorithms employ a population-based search to find many Pareto efficient solutions in a single run. Once the probability of all the linked nodes has been updated by compiling the SIMGES model, the objective function values are returned to the optimization tool and the process is repeated. Consistency is critical to be able to identify a preferred alternative with confidence. In the proposed method, the first step in the consistency check occurs after the evolutionary algorithm has generated a set of non-dominated policy or management options. Usually, solutions generated by the evolutionary algorithm are a good indicator of shortcomings of the network flow model structure. For example, if changes in a node should have an effect on the utility function and this has been ignored intentionally or unintentionally in the SIMGES model, the results generated by EMO will exploit this weakness in the flow network and generate solutions that should have corresponded to higher utility function values.

The objective functions of the problem take into account the maximum deficit of the demands as well as the resilience of the water system. For that, three objective functions are proposed.

The problem can be mathematically expressed as follows.

Given three objective functions:

$$x = f(\beta) \tag{2}$$

$$y = g(\beta) \tag{3}$$

$$z = h(\beta) \tag{4}$$

where x is maximum annual deficit for agricultural demands (MaxDef1Year) (Minimized); y is maximum 10 consecutive years deficit for agricultural demands (MaxDef10Years) (Minimized); and z is years of pumping (Minimized).

These objective functions are optimized by coupling NSGA-II algorithm and SIMGES. Results from this optimization running represent the outcome of SIMGES model. For this reason, these three functions are restricted by the solutions of Equation (1). On the other hand, β represents a combination of n non-ranked and non-weighted management options, which are the decision nodes of the SIMGES model and represent the RC. They also represent the genes of the chromosome of the algorithm:

$$\beta = (g_0, g_2, \ldots, g_n) \tag{5}$$

These n input variables representing RC denote the set of feasible parameters over which the model produces a realistic output. There are therefore j optimized solutions placed at the Pareto front expressed as j combinations of the different operation rules belonging to each input variable:

$$\begin{array}{l}\beta_a = x_a, y_a, z_a \\ \beta_b = x_b, y_b, z_b \\ \ldots \\ \beta_j = x_j, y_j, z_j\end{array} \tag{6}$$

Each β (the RC) is represented by the volume threshold in each month of the OR and the restriction coefficient corresponding to each of them. These variables (volume threshold and restriction coefficient) are discretized at certain intervals. The volume level is between a minimum (5 Mm^3) and a maximum (87 Mm^3) value depending on the associated reservoirs (Sichar and Arenós) and the restriction coefficient varies between 0 and 1 or, in other words, between not applying and applying a total restriction (100%).

Two constraints related to the deficit objective functions were defined:

$$\text{MaxDef1Year} < 50\% \tag{7}$$

$$\text{MaxDef10Years} < 100\% \tag{8}$$

Each evaluation of the objective functions requires the simulation model be run under this operation rule. To do this, the process is as follows (Figure 6). First, the parameters of the EMO and the minimum and maximum thresholds of

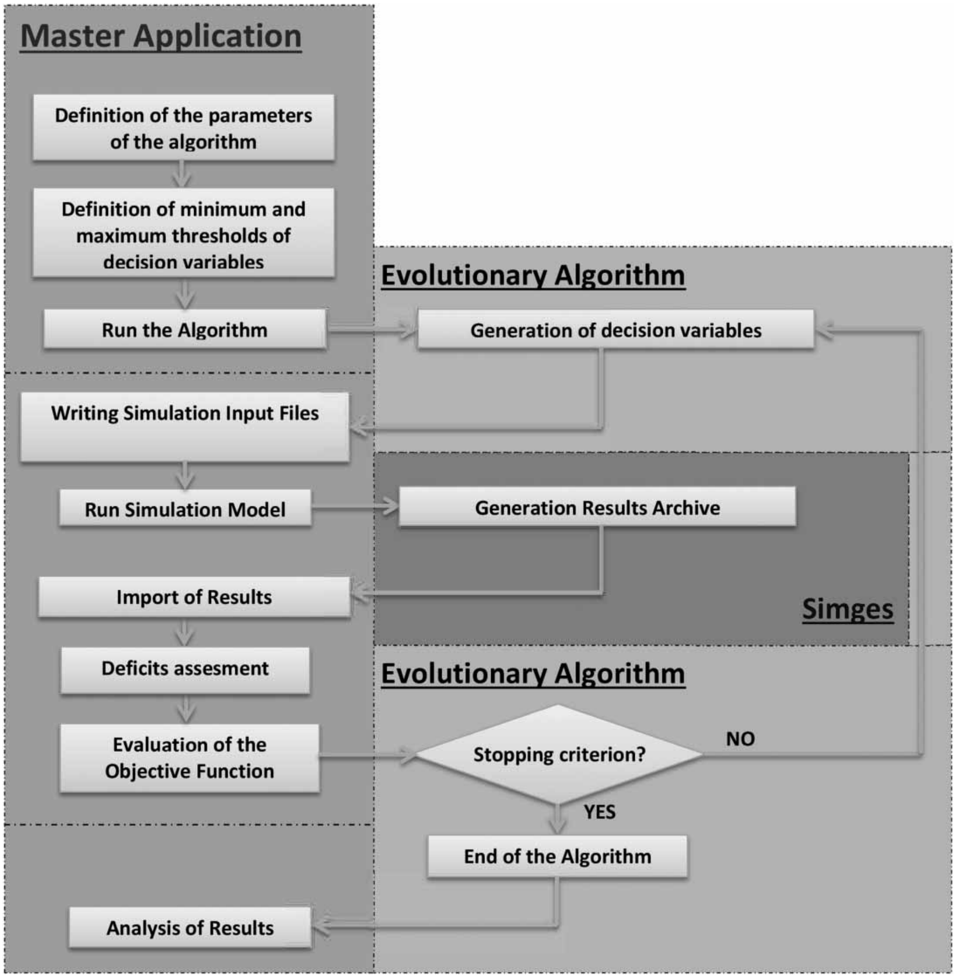

Figure 6 | Schematic model coupling.

the decision variables are defined in a Master Application that is responsible for controlling the whole process. After this, the Mater Application runs NSGA-II, which defines the first individual (set of decision variables), and with these variables the data files needed for SIMGES are created. SIMGES is run, and the Master Application imports the results and calculates deficits. The aquifer pumping allows the OFs to be evaluated, and this value is returned to the optimization model to create the next individual.

Regarding EMO, the initial population for the optimization was 200 with a crossover probability of 0.9, a single-point binary crossover, a bitwise mutation probability of 0.005 and a seed for a random number generator of 0.123457. This setting was the most suitable for handling the problem after developing a detailed test with different configurations.

RESULTS AND DISCUSSION

The results drawn from this analysis are shown in the different figures representing on the one hand the Pareto front that links the different objective functions and, on the other hand, the operation rule parameters that are the decision variables of the algorithm. The results presented here correspond to different tests conducted with the NSGA-II algorithm for the different OR proposed.

Two hundred points are represented in Figures 7–10. Each of these points represents the result applying SIMGES for each combination of parameters obtained using NSGA-II to define the RC mentioned at the beginning of the previous section on 'Coupling of methods'. These 200 points represents an optimized solution for the OFs defined in Equations (2)–(4), RCs parameters or interesting variables

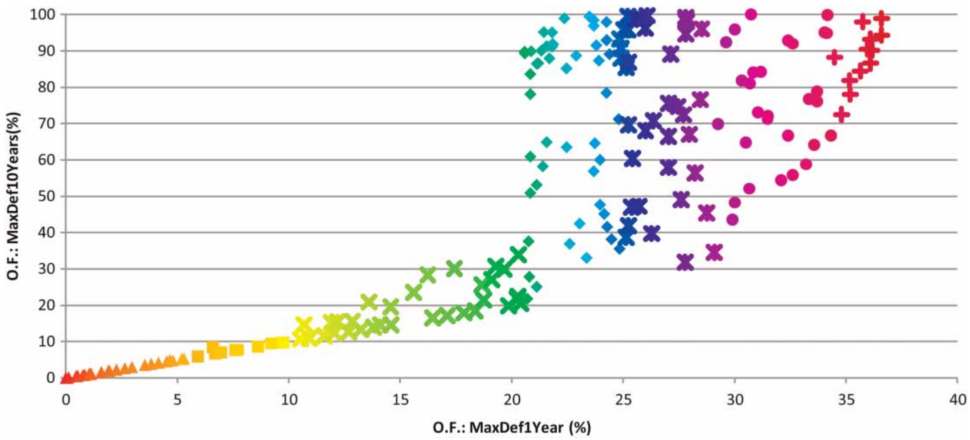

Figure 7 | Pareto front 1; maximum deficits for the agricultural demands (for colour/symbol coding, see Table 2).

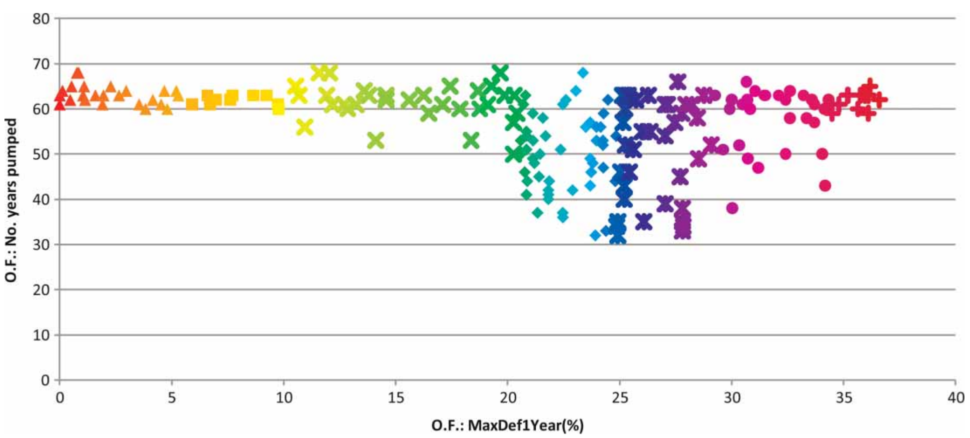

Figure 8 | Pareto front 2; number years pumped versus deficit of the agricultural demands (for colour/symbol coding, see Table 2).

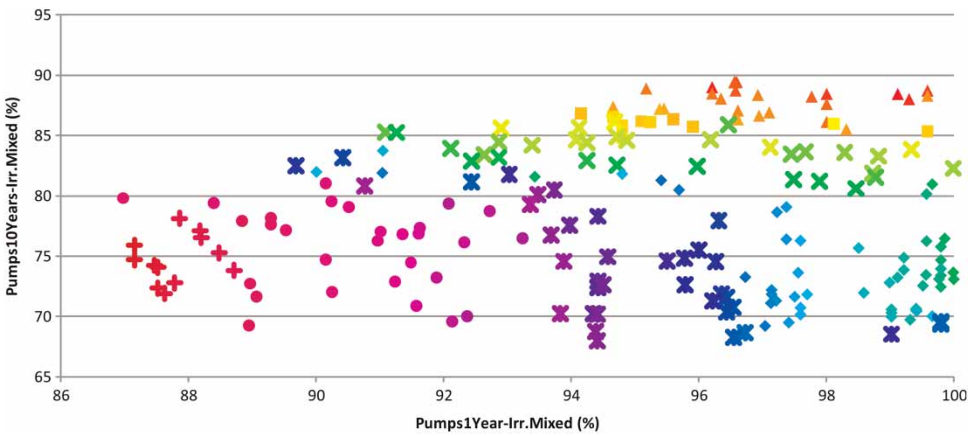

Figure 9 | Maximum pumping of 1 and 10 years for the mixed irrigation (for colour/symbol coding, see Table 2).

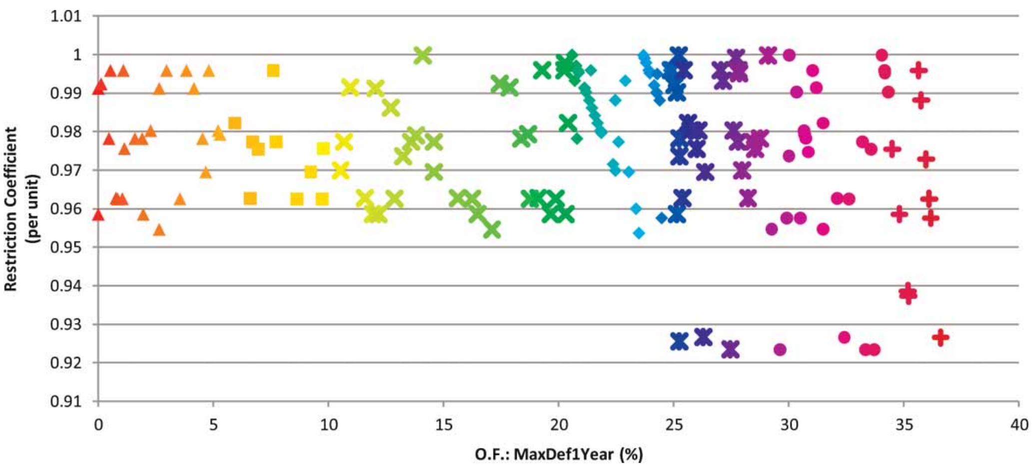

Figure 10 | Restriction coefficient (for colour/symbol coding, see Table 2).

(maximum pumping of the mixed irrigation), drawn from the last population found by NSGA-II algorithm; this is how RCs are obtained. To relate the solutions of one figure to the rest of the figures, a colour scale gradient has been fixed and solutions are sorted according to the maximum annual deficit of the agricultural demands (abscissa of Figure 7). Table 2 lists the colour/symbol coding adopted in Figures 7–11. For example, the points (in any figure) with colours between orange and yellow are related to OR that provide a maximum annual deficit of the agricultural demands between 5 and 10%.

Table 2 | Colour/symbol coding adopted in Figures 7–11

Colour/Symbol	Maximum annual deficit of the agricultural demands (%)
Red/▲–orange/■	0–5
Orange/■–yellow/■	5–10
Yellow/■–green/×	10–20
Green/×–cyan/◆	20–25
Blue/Ж–purple/•	25–30
Purple/•–pink/•	30–35
Pink/•–dark red/+	35–37

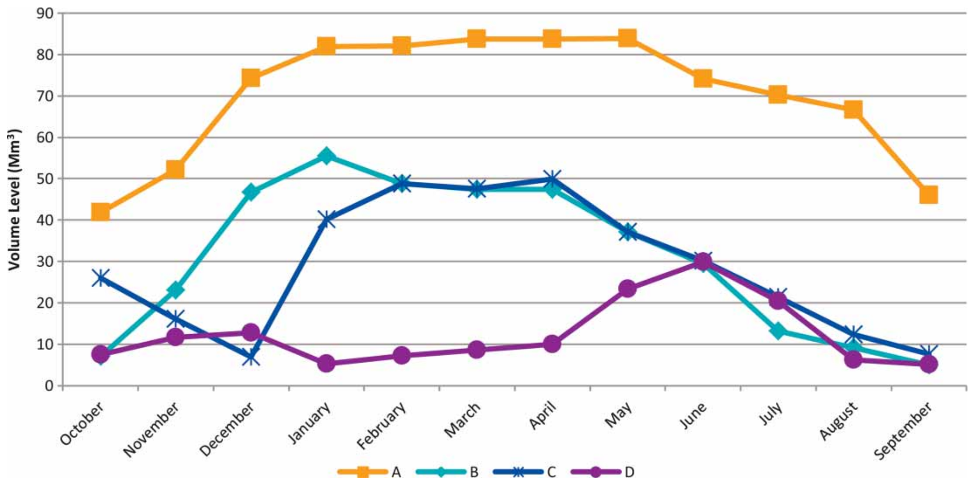

Figure 11 | Curves at the volume level, parameter of the operation rule (for colour/symbol coding, see Table 2).

Figure 7 shows the Pareto front corresponding to the short term (1 year) and the long term (10 years) of the deficit of agricultural demands. Notice that an inferior front can be distinguished by the dispersing point over this line. This OR represents a great variety of possible solutions with deficits ranging from 0 to 36% for the short-term deficit and up to 100% of the long-term deficit (in percentage over the annual demand).

The growing trend of this figure is due to the conditions of the basin: (1) storages in the reservoirs and (2) the fact that agricultural uses with more demand can be supplied with groundwater. The set of demands that can receive groundwater can therefore achieve a state of no deficit. From this situation, and as shown in the figure, increasing the annual deficit implies that the growth also accumulated 10 years of deficit. The optimal solution is not that with zero deficits, and the number of years pumped must also be taken into account.

Figure 8 shows the number of years pumped, sorted according to the annual deficit of the agricultural demands. Note that this figure indicates the number of years of pumping required to achieve specific deficits. This parameter (the number of years) was taken into account because pumping has an associated cost which decreases while reducing the pumping time. It is possible to distinguish three zones in the figure, the first one approximately 0–20% of the annual deficit in which the pump is above 55 years. For fewer deficits it is therefore necessary to pump up to 68 years, which is the number of years simulated. The second zone is associated with annual deficits of 20–28% with 10 years of accumulated deficits ranging between 20–100%, hence the high values of these deficits. By not restricting the demand, constant pumping is not necessary and the number of years pumped decreases to 35. This lower value of years pumped means that no matter which operating rules apply, it is always necessary to pump at least 35 of the 68 years of the simulation because the surface water is not enough to supply the whole water demand of the basin. Finally, the third zone corresponds to a large number of years pumped, but this time the zone is associated with high values of the maximum deficits; this set of solutions is not appropriate due to the high deficits of the demands and the number of pumped years.

In addition to the number of years pumped, it is important to represent the maximum annual pumping of the mixed irrigation facing the maximum long-term pumping of the same demand (Figure 9). The figure shows a scatter cloud of points and much more restrictive intervals of variation of the pumping than for the deficits of the agricultural demands. The annual pumping is 87–100% of the maximum annual pumping and of 10 years of pumping, and 67–90% of the accumulated 10 years of pumping. Very high values for both indicators imply that water is scarce and requires high pumping for agricultural areas of channel 100, channel 220 and María Cristina (mixed irrigation) in order to avoid deficits.

Looking at the colour distribution discussed above, it can be seen that the first stage (0–15% of the annual deficits) of the Pareto front for the deficits is associated with a change of 10 years of pumping between 90 and 84%. The rest of the Pareto front (15–35% of the annual deficits) corresponds to a variation of annual pumping between 100 and 87%. There is therefore an area that varies as a function of 10 years of pumping and another area that depends on the annual pumping.

Figure 10 represents the coefficient of restriction, the OR parameter and the decision variable algorithm depending on the maximum deficit agrarian demands. The obtained restriction is around 100%, more specifically 92–100%, although the largest set of solutions is 96–100%. The figure reveals that a very high restriction has to be applied regardless of the results obtained. However, the restriction also influences the volume level (the other parameter of the operating rules) in these results to be obtained.

In Figures 7 and 8, the 200 points shown in each figure (last population found by NSGA-II) represent two Pareto fronts, the first between the short term (1 year) and the long term (10 years) of the deficit of agricultural demands and the second between the short-term deficit and the number of pumping years.

As mentioned above, there are 200 results that provide different combinations of objective functions. These results translate into 200 RCs obtained by the NSGA-II algorithm. Each of these RCs is a curve defined with 13 values, 12 corresponding to the months of a year and another to the coefficient of restriction. Because representing and analyzing 200 curves is not feasible, and given that some curves are not applicable to real management scenarios because of the complexity and variability of their definitions, four curves have been selected to represent various parts of the Pareto front (Figure 11).

Curve A (filled square/orange in online version) corresponds to solutions close to the origin of Pareto front reference 1 (Figure 7), i.e. the maximum annual deficits and 10 years of claims of 5% of the agricultural environment. This implies, as already explained, a large number of years pumped (Figure 8) and high values of these pumps (Figure 9). To achieve these results, the OR are defined with fairly high levels (compared to the other three curves). When the sum of the volumes of the Arenós and Sichar reservoirs are below those levels (which indicates that the RC of the mixed irrigation are not supplied with the water surface), only traditional irrigation has to be taken into account and mixed irrigation has to pump water. Curve B (diamond/cyan in online version) is associated with annual maximum deficits of 20–25% of the agrarian demands and 30–100% in the case of the maximum deficits of 10 years. This curve is defined with a level lower than curve A, allowing a larger surface to supply the mixed irrigation and, therefore, somewhat less by pumping. Curve C (Cyrillic symbol Ж/dark blue in online version) is similar to B, differing mainly in the first months of the hydrological year, i.e. November to January. Those months can be seen as the curve B reserve supplying more water to the surface for traditional irrigation. However, curve C allows for a greater surface to supply mixed irrigation; for this reason, the traditional irrigation (and therefore the agrarian demands) deficit increases. Finally, curve D (filled circle/purple in online version) corresponds to maximum annual deficits of 25–30% of the agricultural demands and 30–100% in the case of the greatest deficiencies of 10 years. This RC is defined with low levels and is associated with a very small reserve for traditional irrigation, causing high deficits of traditional demands.

Table 3 shows the results (deficit and pumping) of the water system without OR and with RC 'Agreement 70'. The results without OR are not in the solutions of the NSGA-II algorithm because it has a maximum deficit of 10 years of the traditionally irrigated area, which is larger than the limit established in official studies developed by the Jucar Basin Authority. The results with 'Agreement 70' RC follow a similar behaviour to the points marked '×' (green in online version) of the figures, and this curve

Table 3 | Results of deficits and pumping without OR and with the RC Agreement 70

		Without OR (%)	RC Agreement 70 (%)
Traditional irrigated area	Maximum deficit of 1 year	37.12	23.35
	Maximum deficit of 10 years	217.28	55.77
Mixed irrigated areas	Maximum pumping of 1 year	87.4	97.85
	Maximum pumping of 10 years	59.64	73.3

(Figure 3) corresponds to curve C (Figure 11) but with a slightly lower level.

CONCLUSIONS

This paper demonstrates the optimization of operating rules based on the coupling of an EMO with a flow network model. This approach allows a set of rule curves of a reservoir to be obtained for the allocation of water during drought demands. The EMO used was the NSGA-II algorithm. The simulation model was developed with the program SIMGES of the decision support system shell AQUATOOL based on network flow algorithms. The problem that arises is how to reduce the highest annual deficits and the maximum long-term deficits while taking into account the cost of additional pumping. The optimization decision variables are the trigger volume of applying the OR and the restriction coefficient. The coupling methodology is based on the evaluation of the objective function, which represents a run of the simulation model for watershed management to estimate the demand deficits and pumps.

This methodology has been applied to the Mijares River basin, a system that is characterized by severe droughts, a well-established system of rights between users and the possibility of the joint use of surface and groundwater resources. By applying this approach, different types of operating rules have been tested to provide results in terms of deficits and similar pumps. A multi-objective point of view allowed the short and long terms of the deficit and the pumping resource to be taken into account. Moreover, this implementation helps users or managers of the water system to determine the best or most convenient management for the river basin.

ACKNOWLEDGEMENTS

The authors wish to thank the Confederación Hidrográfica del Júcar (Spanish Ministry of the Environment) for the data provided in developing this study, the Comisión Interministerial de Ciencia y Tecnología (CICYT or Spanish Ministry of Science and Innovation) for funding the projects INTEGRAME (contract CGL2009-11798) and SCARCE (program Consolider-Ingenio 2010, project CSD2009-00065) and the Generalitat Valenciana for the Gerónimo Forteza grant (FPA/2012/006). The authors also thank the European Commission (Directorate-General for Research & Innovation) for funding the project DROUGHT-R&SPI (program FP7-ENV-2011, project 282769) and the Seventh Framework Programme of the European Commission for funding the project SIRIUS (FP7-SPACE-2010-1, project 262902).

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First received 24 September 2012; accepted in revised form 6 May 2013. Available online 25 June 2013