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Assessment of evolutionary algorithms for optimal operating rules design in real water resource systems

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Abstract

Two evolutionary algorithms (EAs) are assessed in this paper to design optimal operating rules (ORs) for Water Resource Systems (WRS). The assessment is established through a parameter analysis of both algorithms in a theoretical case, and the methodology described in this paper is applied to a complex, real case. These two applications allow us to analyse an algorithm's properties and performance by defining ORs, how an algorithm's termination/convergence criteria affect the results and the importance of decision-makers participating in the optimisation process. The former analysis reflects the need for correctly defining the important algorithm parameters to ensure an optimal result and how the greater number of termination conditions makes the algorithm an efficient tool for obtaining optimal ORs in less time. Finally, in the complex real case application, we discuss the participation value of decision-makers toward correctly defining the objectives and making decisions in the post-process.

Keywords: Evolutionary Algorithms, Water Resource System, Decision-Makers, AQUATOOL, SIMGES, Management, Optimisation, Operating Rules

1. Introduction

Over the last two decades, Evolutionary algorithms (EAs) have been applied extensively to a number of areas of water resources, such as water distribution systems (Goldberg and Kuo 1987; Savic and Walters, 1997), urban drainage and sewage systems (Guo et al. 2008), water supply and sewage treatment systems (Murthy and Vengal 2006), hydrologic and fluvial models (Muleta and Nicklow 2005) and subterranean systems (Dougherty and Marryott 1991), as highlighted in a review by Nicklow et al. (2009). However, while EAs have been applied successfully to many academic problems, additional research is required to enable them to be applied in real-life context (Maier et al., 2014). For example, there is a need to determine which searching mechanisms and termination/convergence criteria are best for real-life problems and the best way to convey the results of the optimisation process to decision makers (Maier et al., 2014). Consequently, these issues are the focus of this paper.

Simulation models are the most commonly used tool to analyse the integrated planning and management of WRS. These models allow for more detailed representations of the systems than do the optimisation models (Loucks and Sigvaldason, 1982). Moreover, the applicability of optimisation models to system management for most real reservoirs is limited due to the "high level of abstraction" needed for the efficient implementation of optimisation techniques (Akter and Simonovic, 2004; Moeni *et al.* 2010).

Normally, simulations of water management systems use operating rules (ORs) to model the efficient management of water resources. Designing and obtaining ORs for multi-reservoir systems is a complex task and has been widely developed during the scientific history of water resource studies (Young, 1967; Bhaskar and Withlach, 1980; Lund and Ferreira, 1996). On the other side, ORs must be implementable in real applications and therefore need to be robust as well as simple to be defined by a set of indicators and parameters.

A common technique used to design ORs is based upon iterative simulations of water management models. In this case, the goal is to find an OR that optimises system management. Therefore, the iterative process to find such an OR can be controlled by an optimisation algorithm that is responsible for varying the OR parameters based upon the results obtained from the simulation. EAs afford several benefits compared with classical optimisation techniques because they can be implemented without heavy a-priori model requirements, and thanks to their ability to manage discrete variables, EA optimisation procedures can directly address alternatives when applied to OR optimisation. To this end, EAs present effective an optimisation algorithm for searching for optimal rules in WRSs. For example, Oliviera and Loucks (1997), and later Ahmed and Sarma (2005), presented an approach for the optimisation of ORs in multi-reservoir systems using EAs. Other cases are reported by Cai *et al.* (2001) to solve nonlinear models of water management using a combination of an EA and linear programming; by Momtahen and Dariane (2007), who used a direct search approach to optimize the parameters of reservoir operating policies with a EA as an optimization method; or by Elferchichi *et al.* (2009), who applied an EA to optimise reservoir operations in the Sinistra Ofanto (Foggia, Italy) irrigation system. Furthermore, in the literature were used another metaheuristic approaches such as Guo *et al.* (2013), who incorporated a multi-population mechanism into a non-dominated sorting particle swarm optimization to obtain optimal rules for a water-supply reservoir; or as in Hossain and Shafie (2014) where a nonlinear reservoir release optimization problem was resolved by comparing evolutionary methods and swarm intelligences.

The main purpose of this paper is to test EAs and scattered search approaches to design ORs that optimise WRS management. The EAs used are the SCE-UA (Duan *et al*. 1992) and the Scatter Search (Glover, 1997), which are combined with the SIMGES network flow simulation model to design optimal ORs. In addition, an analysis of the parameters of both algorithms is carried out, which allows us to determine which termination/convergence criteria are most appropriate for realistic problems, apart from showing the most influential parameters that affect the optimisation process. On the other hand, the previous analysis and the use of one of these EAs in a real complex case demonstrate which of the two studied algorithms is the best for solving this type of problem. Finally, a method of transmitting the optimisation results is presented to make the decision-making easier. To analyse the parameters, a simple theoretical model representing a fictitious WRS is used. In the application for a real complex WRS, the Tirso-Flumendosa-Campidano system located on Sardinia Island (Italy) is used.

2. Materials and Methods

We propose a connection between EAs (SCE-UA or Scatter Search) and a traditional water allocation model (SIMGES) in the water resources field to design optimal ORs for real WRSs. The approach developed is detailed in Figure 1. Decision variables, OR parameters, are defined by the user and are sought by the EA to design optimal ORs for the WRS to which it is applied.

Moreover, some algorithm-specific parameters, such as population size, the number of subgroups or the maximum number of iterations should be indicated to the EA, apart from the decision variables, to allow optimisation. Every EA implements the optimisation process as outlined below; the EA generates several individuals (or solutions) that belong to an OR collection. In our case, each OR aptitude depends on how it affects the WRS management. For this reason, WRS management is simulated through the SIMGES network flow for each OR, and the obtained results allow the EA to evaluate the objective function (OF). Given the value for each individual (or solution) of that OF, the algorithm obtains new values for the decision variables defining the OR, and the process is repeated until the stop condition for each EA is fulfilled.

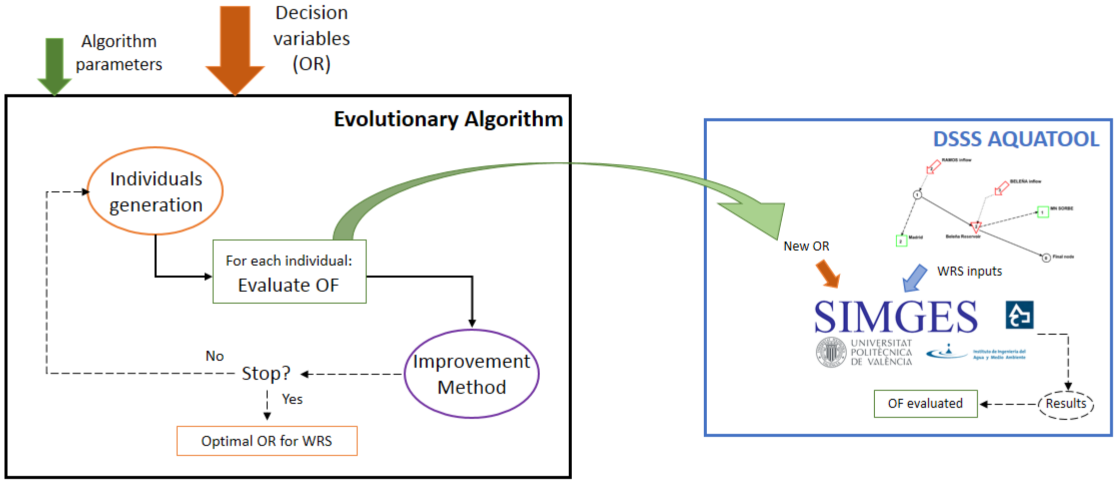


Figure 1: Methodology. EA combined with the network flow SIMGES.

Both algorithms have been repeatedly used in different areas of research. The SCE-UA algorithm is implemented in this study due to its demonstrated efficiency, which has been widely recognised in calibrating hydrological problems with a large number of parameters and with a high nonlinearity (Duan *et al.*, 1992; Luce and Cundy, 1994; Kuczera, 1997; Boyle *et al.*, 2000). On the contrary, the use of the Scatter Search application to design OR is currently uncommon but has been successfully applied in distribution network calibration problems (Liberatore and Sechi, 2009) as well as a wide range of more general optimisation problems (Martí, 2006; Campos et al, 2001; Scheuerer and Wendolsky, 2006; Adenso-Díaz *et al.*, 2006). However, we have chosen the second algorithm because, unlike most conventional EAs such as the SCE-UA, thanks to the adoption of search and selection techniques, the population is much smaller than when using other EAs.

2.1. SCE-UA algorithm

The SCE-UA optimisation mechanism (the Shuffled Complex Evolution) was developed by Duan *et al.* (1992) at the University of Arizona. As mentioned above, its efficiency has been successfully tested to calibrate problems of hydrological models with a large number of parameters and with a high nonlinearity. The basic operation of the SCE-UA algorithm, inspired by the principles of natural selection and genetics, is a combination of deterministic and random processes. The departing point is from different search points (*individuals*) that are organised by teams (*complexes*). Searching for the globally optimised solution, an evolutionary process (evolution) is designed. This process is based on different reproduction methods such as crossing, mutation or recombination, and team mixing (shuffle). An extended SCE-UA technical details can be found in Duan *et al.* (1992).

2.2. Scatter Search algorithm

The Scatter Search algorithm (Glover, 1997) is a metaheuristic procedure based upon formulations of strategies for generating candidate solutions, and thanks to the adoption of search and selection techniques, the point population used is much smaller than is necessary for other techniques. The concepts and principles of this method are based on the strategy of combining decision rules. The Scatter Search operates on a set of solutions, called the Reference Set, and combines them to create new solutions that improve the original ones. In this sense, the Scatter Search should be considered as an EA. However, contrary to other evolutionary methods, such as genetic algorithms, the Scatter Search algorithm is not based upon randomness over a relatively large group of solutions but is based upon systematic and strategic choices over a small group. Typically, genetic algorithms consider large population sizes (100 solutions as an order of magnitude), whereas the Scatter Search utilises an equivalent set of only 10 solutions.

It is worth noting that the Reference Set retains the "good" solutions, but the meaning of good is not restricted to the quality of the solution; the diversity given to the Reference Set is also taken into account. The optimisation path is guided by the gradual inflow of data on the admissible solutions level and in its neighbourhood. Indeed, Scatter Search can acquire information both from the points "visited" and from those generated separately through flexible management of the problem's data set.

One of the most interesting characteristics of the Scatter Search is that it integrates the combination of solutions with the local search. This local search can contain a memory structure, although it is not needed. In most cases, it is simply implementing a conventional local search.

Figure 2 shows the baseline method diagram. The detailed process that is followed by the Scatter Search starts with the generation of a collection P of several solutions. This group of solutions is improved through local search, although if the obtained solution does not improve the results, the initial solution is maintained. Once group P is generated and improved, the Reference Set is applied, following given criteria, including the quality of the solutions and how different they are to each other (quality and diversity). The Reference Set solutions are evaluated and ordered from best to worst with respect to the fitness values.

The Reference Set is divided into subgroups. A simple method to generate these subgroups consists of creating all couples that can be formed with the elements of the Reference Set, but these subgroups can be formed by three-person groups or by any other solution sizes. Once these subgroups are designed, the solutions are combined to find new solutions. These new solutions are obtained from combinations that can be either immediately introduced to the Reference Set (dynamic actualisation), or temporarily stored in a list until all the combinations are formed to analyse which solutions are finally chosen for that Set (static actualisation). Note that the algorithm stops when it attempts to combine solutions, and the Reference Set is empty.

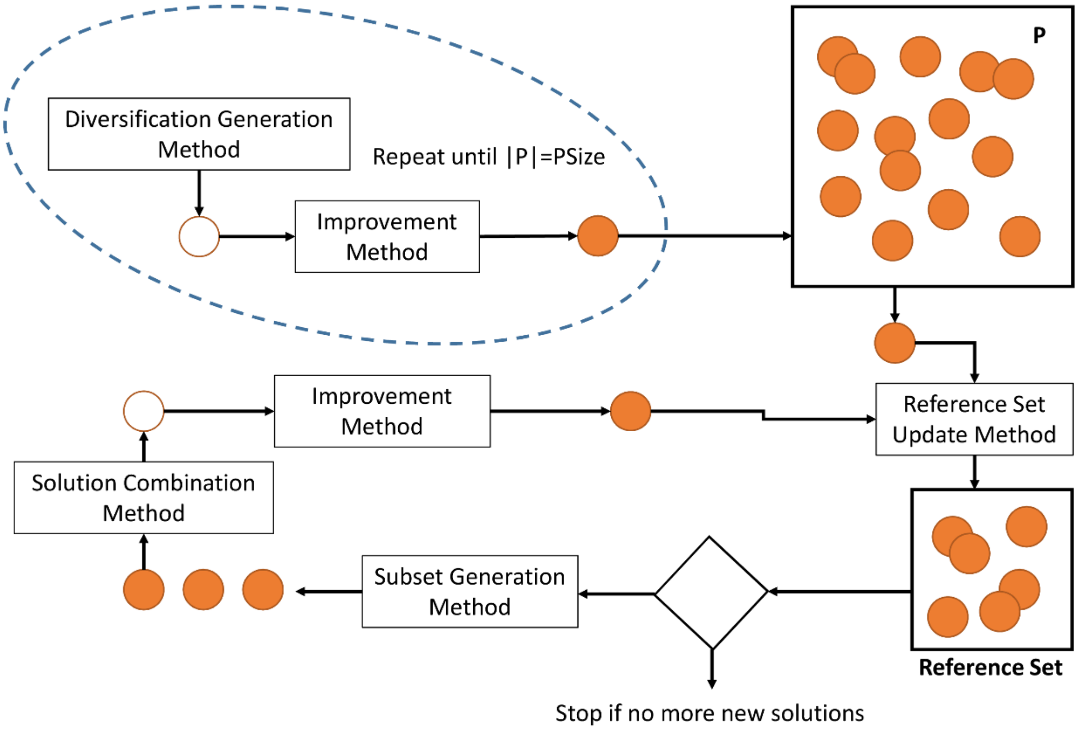


Figure 2: Flowchart of Scatter Search algorithm (Adaptation of Martí and Laguna, 2003).

2.3. Water allocation model

To design an optimal OR, we combined EAs with the water allocation model SIMGES (Andreu *et al.*, 1996), which is responsible for evaluating the management of WRS. SIMGES is a module of the Decision Support System Shell (DSSS) AQUATOOL (Andreu *et al.*, 1996). The DSSS AQUATOOL includes different modules, apart from SIMGES, for evaluating the water quality of water bodies and for evaluating probabilities for drought analysis and drought risk assessment. This DSSS and its SIMGES model have both been extensively used for water basins in Spain (Júcar, Segura, Tajo, etc.) (CHJ, 1998; MIMAM, 2004; Andreu *et al.*, 1996) and in other countries (e.g., Argentina, Chile, Brazil, Italy, Bosnia, Cyprus, Algeria). Generally, a DSSS facilitates the negotiation of socially conflicting decisions by users and stakeholders (as the implementation of environmental flows) and helps decision-makers in their task.

The SIMGES model transforms the WRS into an internal network flow optimisation problem that is solved for every time step (step-by-step) to find a flow solution compatible with the physical constraints, system priorities and other management constraints. An OF is used to solve this network flow, evaluated as a sum of different terms that depend on the type of element (reservoir, demand, arcs, etc.). A simplified OF example (F_{rd}), for the case of reservoirs and demands, is shown in Equation 1. F_{rd} is minimised to optimise the water allocation problem.

$$F_{rd} = \sum_{i=1}^{R}\left(\sum_{j=1}^{L}\left(V_{j,i}\left(C_j + PR_i\right)\right) + Sp_i C_{sp}\right) + \sum_{k=1}^{D} DD_k\left(C_{DD} + PD_k\right) \qquad \text{(Eq. 1)}$$

where R is the number of reservoirs in the network flow, $V_{j,i}$ is the volume at level j for reservoir I, L is the number of levels in a reservoir, C_j is the benefit/cost of water storage at level j and PR_i is the priority number for reservoir i. The last part of the reservoir term is defined by Sp_i, which is the probability of a spill to the reservoir i, and C_{sp}, which is the cost of spills to the reservoirs. The second term of F_{rd} is associated with demands. D is the total number of demands, and DD_k is the deficit of demand k. The cost associated with the deficits of demand is C_{DD}, and PD_k is the priority of demand k. Eq. 1 is composed of costs (set by default and previously calibrated) and priorities that the user can change.

Furthermore, the SIMGES model allows a user to define ORs to model decision-making based upon specific indicators. Examples of some of these indicators are the stored volume in one or more reservoirs and the accumulated in-stream flow during several months at one or more points within the system. The application of these ORs includes the restriction to a certain percentage of one or more demands, environmental flow or the pumping system. This type of OR is used to anticipate droughts to avoid dramatic failures of the WRS.

2.4. Optimization problem's statement

The optimization problem carried out in this paper to obtain optimal operating rules involves different statements like the EA's parameters, the OR to optimise, the OF or the problem restrictions.

Both algorithms analysed in this manuscript have several parameters that affect the performance of the optimization process, and for each algorithm, these parameters are analysed in section 3. Moreover, the aim of the optimization is to find an optimal OR, which is defined by some parameters such as the volume stored in a reservoir or the restriction coefficient to supply more or less amount of water to a demand. Depending on the case analysed (theoretical – section 3 or real – section 4) the OR may be defined with different amounts of parameters. The OR's parameters are the decision variables of the EA and they will be defined in the appropriate section.

Furthermore, the algorithms use an OF to optimise the problem. Scatter Search and SCE-UA are single-objective algorithms. For this reason, in the real case studied in the document, the OF is a combination of several objectives. The main objectives will be related, for each case, to the demands (deficits) or to the pumping system (economic cost).

In addition, WRS usually have legal restrictions such as reliability criteria of the demands or economic bounds. These type of restriction are considered in the theoretical and real cases.

3. Parameter analysis

In this section, an analysis of the aforementioned EA is carried out. This analysis studies the influence of the SCE-UA and the Scatter Search parameters when used as a tool to design optimal ORs in WRS. According to Duan et al., (1994), the effectiveness and efficiency of an algorithm are influenced by the choice of the algorithmic parameters. Typically, these algorithms have a higher or lower number of parameters and provide a certain flexibility, i.e., these parameters determine the algorithm performance and allow the user to decide how the algorithms should work. Examples of these parameters are aspects related to the stopping criteria of the optimisation process (maximum number of iterations, variation percentage of the OF or the decision variables, etc.), population size, number and size of the subgroups in which the population is divided to evolve, seed for the calculation of random numbers, etc.

This analysis aims to determine which parameters are the most influential ones to the OR optimisation process. This will allow us to identify which parameters should be specially treated when defining them in new optimisation processes, and eventually, it will enable us to conduct several optimisation processes by modifying those parameters for the specific problem to obtain optimal results.

To this end, a group of optimisations (OPT) is carried out, modifying parameters in each group. Each optimisation is implemented following the methodology described in the previous section. A fairly simple WRS has been used, which is likely a naïve simplification of reality. This system is modelled through SIMGES and is composed of a reservoir, two demands and two inflows to the system (Figure 3). The demand with greater priority (demand 1) and, therefore, the one that should be supplied first, is the one located downstream of reservoir 1. Given the system conditions, it is not possible to supply both demands completely; however, it is possible to supply enough for demand 1 at the expense of not providing any water to the other demand (demand 2) during some time period. This result is typically unacceptable; thus, we look for an OR in which the imposed reliability level for demand 1 is assured while maintaining the maximum possible volume of water supplied to demand 2, as the system allows. In general, for this type of problem, the OF is defined to minimise the deficit of the demands or to maximise the water supplied to them. For this simple case, it is assumed that the supply to demand 1 meets the vulnerability criterion if the maximum annual deficit does not reach 50% of the target annual assignment.

Restriction:

$$Maximum\ Annual\ Deficit\ (\%) \leq\ 50\%\ Target\ Annual\ Assignment \qquad (Eq.\ 2)$$

To obtain this water allocation, an OR is defined in the system for the stored volume in the reservoir. If the stored volume in the reservoir is above a certain threshold (to be optimised), a certain percentage (to be optimised) of the assignment of demand 2 is supplied. Therefore, a simple OR is considered for this analysis and is defined using two parameters (EA decision variables).

OR (decision variables):

$$DV1 = Threshold\ of\ the\ Stored\ Volume\ (Reservoir\ 1) \qquad (Eq.\ 3)$$

$$DV2 = Restriction\ coefficient: Assignment\ percentage\ (Demand\ 2) \qquad (Eq.\ 4)$$

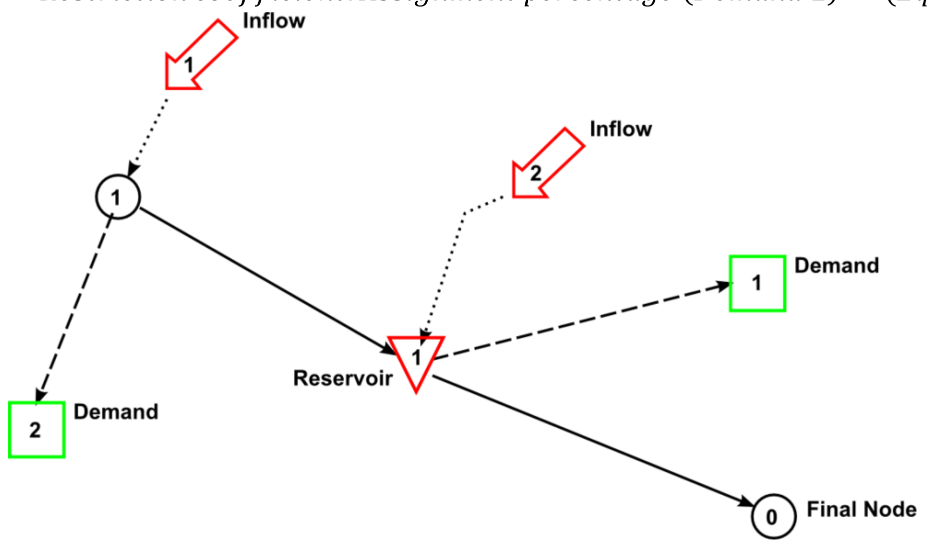


Figure 3: Diagram of the example used for the analysis of the algorithms.

Once this simple example and the purpose for analysis are explained, we will discuss how the EA must maximise the resources supplied to demand 2. With this intention, an OF is defined and evaluated using the following expression, as long as the vulnerability criterion for demand 1 is assured:

$$OF = \frac{Annual\ average\ supply\ of\ Demand\ 2}{Annual\ assignment\ of\ Demand\ 2} \qquad (Eq.\ 5)$$

The best value for this OF term (Eq. 5) is 1, when demand 2 is completely supplied, and 0 is the worst value, representing the case in which no water resources are supplied to demand 2.

3.1. The SCE-UA parameter analysis

The basic parameters that the SCE-UA optimisation process depends upon are specified in Table 1. The maximum number of OF evaluations (MAXN), as will be seen in the several optimisations carried out, has not been necessary to modify its value, at least in the simple system used for this analysis. In complex optimisations requiring a high number of decision variables, there will be a need for a large number of iterations and thus a large number of evaluations of the OF as well. In these cases, it is advisable to adjust the MAXN to limit the maximum algorithm process time. The influence of the other five parameters is not trivial, which is why they were also analysed.

This analysis is formed using five groups of optimisations, one for each parameter in Table 1 (except for MAXN, as previously mentioned). In the first group, 12 optimisations have been carried out in which the NGS parameter has been modified. This NGS has been the first parameter in the analysis because, a priori, it seems to affect the obtained result the most. In the second and subsequent groups, KSTOP, PCENTO, ISEED and IFLAG have been modified.

Table 1: Parameter description and initial values considered in the SCE-UA analysis.

Description	**Parameter**	**Initial Values**
Maximum number of function evaluation	MAXN	10000
Number of shuffling loops in which the criterion value must change by PECNTO before optimisation is terminated	KSTOP	10
Percentage by which the criterion value must change in KSTOP shuffling loops	PECNTO	0.1
Number of complexes (sub-populations)	NGS	3
Random number	ISEED	123456
Considering initial parameters	IFLAG	1

In the first group of optimisations, some parameter values are defined (Table 1), based upon several simulations that have been performed with the SCE-UA algorithm for the calibration of different types of parameters.

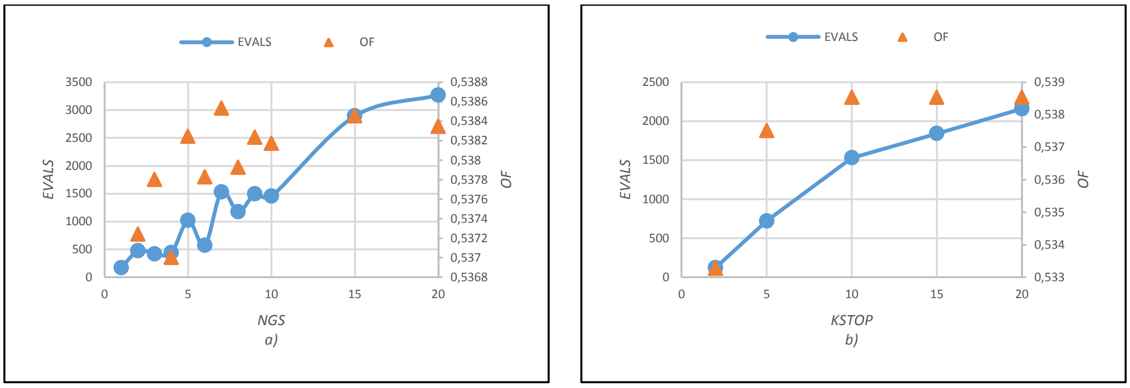
Table A1.1 summarises all the optimisation processes carried out in the SCE-UA analysis, showing the value of each parameter, the number of OF evaluations reached in each trial (EVALS) and the OF value.

The numbers of subgroups (NGS) in which the SCE-UA sample is divided to find new improved individual in the first OPT are 1-10, 15 and 20. A great number of possibilities have been analysed, focusing on divisions below 10 NGS, and two higher NGS values are subsequently tested. Figure 4a shows the evolution of EVALS and the OF according to the NGS. If we consider first EVALS obtained, an increasing trend is observed when the NGS increases. For sizes smaller than 10 NGS, EVALS is below 1500; for sizes larger than 10 NGS, this number substantially increases, reaching more than 3000 OF evaluations. However, in the first 10 OPT, the evolution is not completely linear; for example, a lower EVALS is obtained with 6 NGS than with 5 NGS.

EVALS alone does not allow us to correctly analyse the algorithm because it does not show us how optimal the identified solution is in reality. For that reason, the figure also shows the OF value, which represents the fitness reached in each OPT. It is worth noting that the range of OF values is quite narrow (Figure 4a), between 0.537 and 0.539, which means that different OPT could reach quite similar results. Similarly, as often occurs with the evolution of EVALS, the OF does not follow a linear, positive trend. It is observed that the OF value is lowest when NGS=1 (not shown in Figure 4a because it requires an OF value of 0.534), 2, or even 4. For values above 5 NGS, the OF values obtained are higher and thus represent better solutions. The optimal result of this group of OPT is obtained with an NGS=7, requiring nearly 1500 evaluations and resulting in an OF value of 0.5385.

With this solution, the KSTOP parameter is analysed. This parameter has been modified using the following values: 2, 5, 10 (GROUP=1), 15 and 20. Figure 4b shows the results obtained. In this figure, an increasing trend of EVALS is observed when KSTOP increases. This is normal because a hard stop criterion is defined for the algorithm. For the KSTOP value that is double the value analysed in GROUP=1 (that is, KSTOP=20), the EVALS required is lower than double that required for a KSTOP=10, which shows that it does not follow a completely linear evolution. For the lowest values of KSTOP, the increase for EVALS is greater than the increase for higher KSTOP values. Regarding the OF values reached, for KSTOP values lower than 10, the OF value was below 0.538; however, for KSTOP, the values of 10, 15 and 20 resulted in the same OF value (0.5385).

With the same parameters as in OPT=7, the PCENTO parameter is analysed. In this OPT group, the values adopted for PCENTO were 0.05, 0.1 (GROUP=1), 0.2 and 0.5. Figure 4c shows the results for this parameter. Contrary to the two previous parameters analysed, when the PCENTO value increases (the term condition is less restrictive), EVALS is reduced along with the OF value. For values of 0.05 and 0.1 for PCENTO, the same result is reached, both for EVALS and the OF value. Similarly, for the values of 0.2 and 0.5, the OF reaches the same value, and EVALS is nearly the same; however, because the algorithm ends earlier, the results are worse than in the other case.



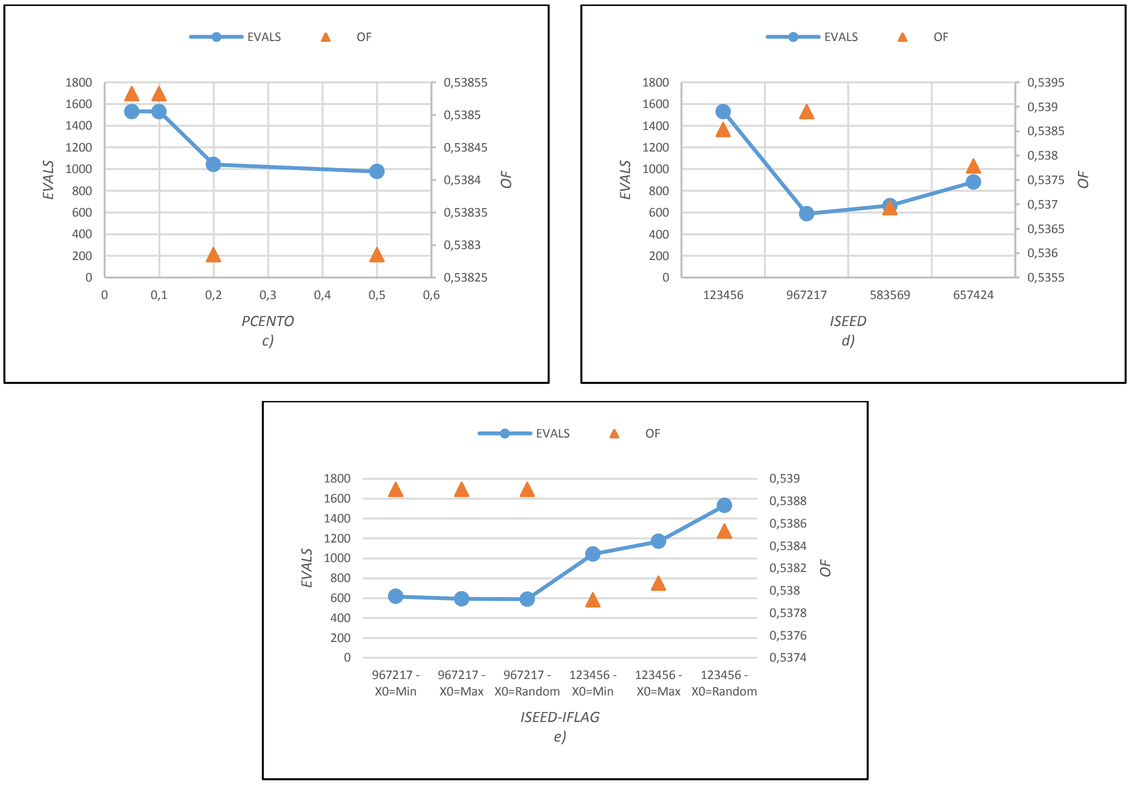


Figure 4: Performed test with SCE-UA algorithm.

The next parameter studied is the ISEED, which is related to the random number generation upon which the algorithm is based. Apart from the ISEED analysed in GROUP=1 (123456), three others have been considered, as shown in Figure 4d. The ISEED affects the obtained results without a clear criterion, i.e., there are ISEEDs with high OF values and high EVALS; others with low values for both of them; and still others with high OF values and low values of EVALS (the best scenario). In these OPT, the optimal result is reached with a seed of 967217, an OF value of 0.5389 and 589 OF evaluations.

The last parameter analysed is IFLAG, which allows the user to consider initial values (X0) or random values for the decision variables. For this group of OPT, the ISEED of GROUP=1 has been used, and the ISEED with the best result originates from GROUP=4. The minimum, the maximum or a random value for each decision variable have been considered as the initial value for both ISEED parameters. Figure 4e shows how the initial values affect the result, depending upon the ISEED. In the case with the best results for ISEED (GROUP=4), the initial value does not affect the result, and in all cases, the same EVALS and OF value are returned. By contrast, with the ISEED from GROUP=1, for which random initial values and a higher EVALS are required (compared to the minimum or maximum initial values), higher values of the OF are obtained.

3.2. The Scatter Search parameter analysis

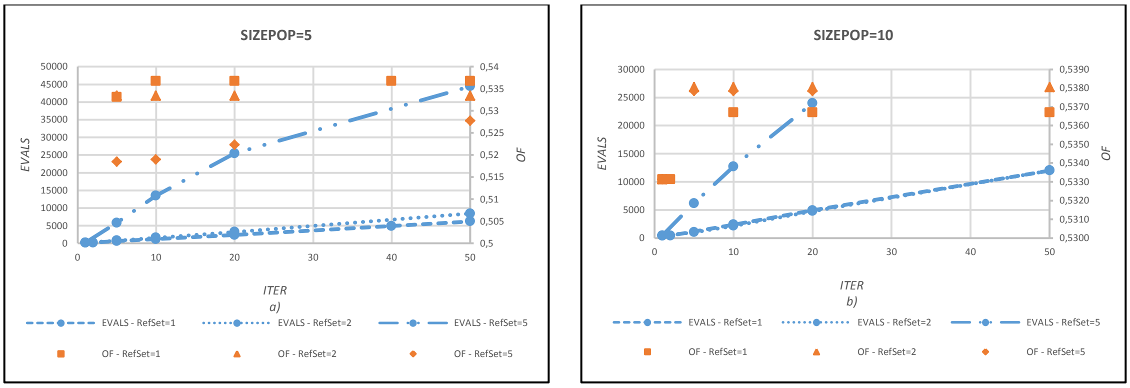
The difference for SCE-UA is that the Scatter Search only needs to define (in the basic configuration) the size of the population (SIZEPOP), Reference Set (REFSET), and number of iterations (ITER).

For this algorithm and in the WRS field, we do not have initial values from experience, and only the explanation in section 2.2 is considered, where it is discussed that this algorithm often works with a small SIZEPOP, typically of 10 individuals, and a small value for the REFSET.

In contrast of the SCE-UA algorithm analysis, and for the reasons mentioned above, a higher number of optimisations have been conducted for this algorithm to analyse its parameters (see Table A1.2). Nevertheless, they have been collected in 4 GROUPS, depending on SIZEPOP. In the first group, a value of 5 is adopted, and the size of REFSET and ITER vary. Figure 5a shows EVALS and the OF value reached in each OPT. On the one hand, it is observed that EVALS increases as the ITER parameter increases for three REFSET sizes (1, 2 and 5). These values for REFSET have been chosen because they were lower than the value for SIZEPOP, and in an extreme case, they have the same value. For the three values of REFSET, it is observed that EVALS increases, which is even more important for the REFSET=5 case. Note that in those OPT, a very high EVALS (more than 5000) is needed to reach the stopping point for the algorithm, except in the case of ITER=1, in which the algorithm ends with 164 OF evaluations without finding any valid solution. For REFSET values of 1 and 2, the trend is almost the same, reaching the requirement of more than 8000 OF evaluations in the case where ITER=50. However, for ITER values below 20, this number is reduced to less than 3300 OF evaluations, with nearly 1600 evaluations for ITER=10 and almost half that value for ITER=5. Figure 5a also shows the OF values, which are between 0.52 and 0.537. It is worth noting that for REFSET=5, in which a high EVALS value was required, the OF result is worse than that obtained with REFSET equal to 1 and 2. The best result (OF=0.5367) was obtained with REFSET=1 and 10 ITER (or more).

The second GROUP of OPT has been carried out with SIZEPOP=10. In this case, the initial values of REFSET have been kept, to see if they are affected by the increasing of SIZEPOP.

Figure 5b and Figure 5a are similar in regard to EVALS. For values of 1 and 2 for REFSET, the trend is almost the same in either case, reaching more than 10000 OF evaluations for a value of ITER=50. Moreover, for REFSET=5, the increase in EVALS is larger, although slightly lower than that for SIZEPOP=5. However, the OF value does not similarly evolve, in this group of OPT; for REFSET=1, the solutions obtained are less optimal than those for the other two values, which obtained almost identical values for the OF (0.5378) using values for ITER greater than 5.



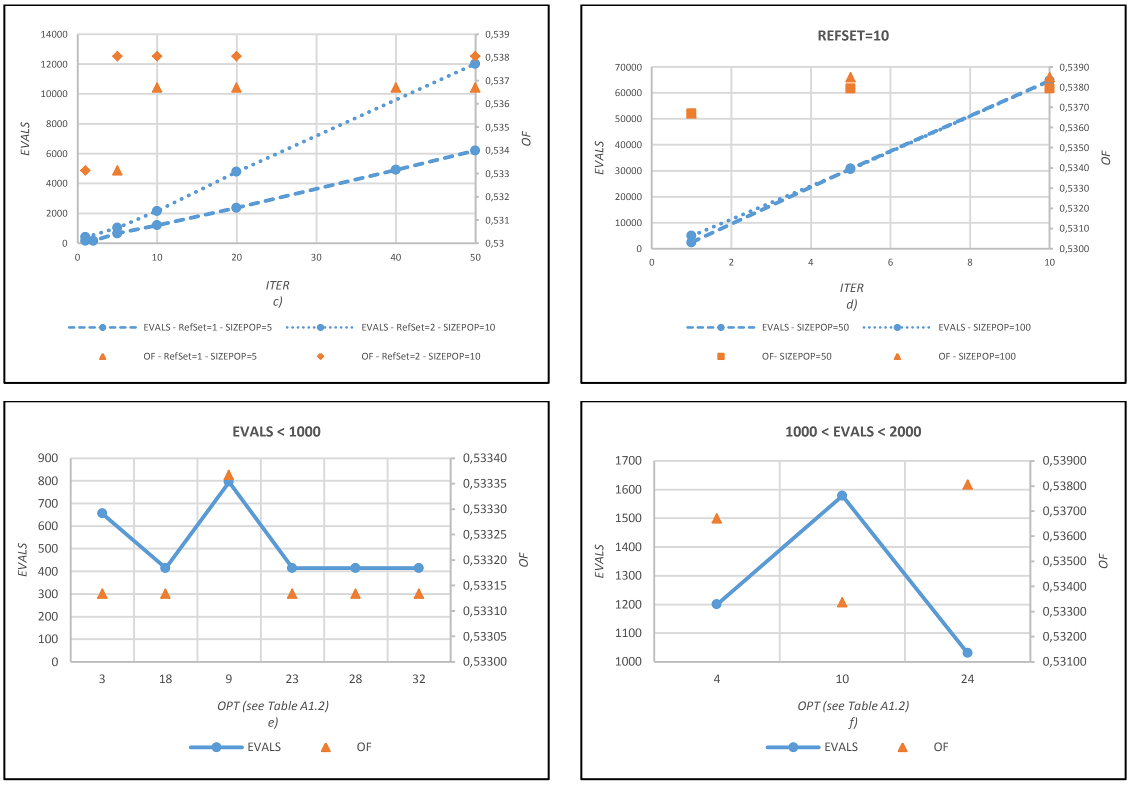


Figure 5: Performed test with Scatter Search algorithm.

To summarise these two groups of OPT, Figure 5c shows the most optimal solutions of each GROUP. For the first group, SIZEPOP=5 and REFSET=1 were used, and for the second group, SIZEPOP=10 and REFSET=2. It is clear to see that the proportion SIZEPOP/REFSET is maintained. Considering both solutions, SIZEPOP=10 is the one with the best value for OF but requires a higher EVALS value. The optimal solution is obtained with SIZEPOP=10, REFSET=2 and 5 ITER, requiring 1030 OF evaluations and reaching an OF value of 0.5380.

Subsequently, we analysed the Scatter Search behaviour for higher values of SIZEPOP, specifically sizes of 50 and 100. In both cases, a value of 10 has been chosen for REFSET size, a lower value than SIZEPOP to maintain the proportion of SIZEPOP to REFSET that was used in previous OPTs. The result shown in Figure 5d reflects the need for a very high EVALS value (from 2377 to more than 64000). With the lowest EVALS value, an OF value of 0.5367 is reached, which is a worse result than that generated through a previous analysis. An OF value of 0.5385 is obtained only for EVALS values higher than 30000 OF evaluations (the highest registered value in the Scatter Search analysis).

With the Scatter Search study, we check to see if higher values of EVALS are reached in many OPT, which is not desirable because it is related to a higher computation time. To compare to the ranges of EVALS obtained with the SCE-UA, Figures 5e and 5f show some OPT conducted with the Scatter Search. Figure 5e shows 6 OPT with fewer than 1000 OF evaluations, with OF values lower than 0.5334. Figure 5f shows 3 OPT requiring between 1000 and 2000 OF evaluations. In those cases, an OF value of 0.538 is reached, with 1030 OF evaluations, although this is worse than the best result of the SCE-UA (0.5389).

3.3. Discussion

The assessment of both algorithms yields some conclusions about the parameters, the stop condition of the algorithm, and which algorithm obtained the best results in this simple case study. Zielinski *et al.* (2005) provide six convergence/termination criteria for EAs. These EAs use some of these criteria, the SCE-UA uses three of them, and the Scatter Search uses only one.

In the SCE-UA, six parameters have been studied, although MAXN has not been used in the analysis because it was not limiting for the example, as mentioned above. From the other five parameters, two of them affect the stopping criteria (KSTOP and PCENTO), one affects the improvements of individuals (NGS), and the last two (ISEED and IFLAG) condition the initial values for the decision variables and generate new values as the individuals evolve.

On the one hand, the NGS parameter has an influence on EVALS and thus on the optimisation time, and on the other hand, it affects the obtained result in certain ways. The results obtained in section 3.1 show that it is not convenient to choose either a low or a high value for NGS in the first case because of worse values for OF and in the second because EVALS increases. Therefore, NGS values between 3 and 8 would be appropriate.

Parameters affecting the convergence/termination criteria (KSTOP and PCENTO) are important. Choosing an incorrect value can make the algorithm end before it is convenient, and sub-optimal results will thus be reached, or, on the contrary, more time will be taken to complete the algorithms than is strictly needed to reach the optimal solution. In the former case, if some slack is introduced to the stop criteria, the process can finish in a shorter time, but it will not be certain if the result is a globally optimised value. However, in the latter case, EVALS will increase because it is quite strict in the termination condition of the SCE-UA, using a higher computation time than would be necessary if these parameters were appropriately defined. PCENTO is the most influential parameter.

Regarding ISEED and IFLAG, they have a certain random nature. A priori, better or worse results can be obtained depending upon the practical case and this randomness.

A more rigorous method has been developed to corroborate the two previous analysis. This method is the ANOVA statistical analysis, which enables us to know the statistical significance of the parameters analysed. The tables below (Table 2 and Table 3) show the results of this analysis, identifying the statistical significance of each parameter analysed (independent variables) versus EVALS and OF value (dependent variables). Low values of this significance indicates a higher probability that the dependent variable values (EVALS or OF) are modified when the value of the parameter analysed is changed.

With this aim, SCEUA algorithm has been used in a larger sample than in the previous section, with a total of 180 OPT (which includes OPTs of Table A1.1).

Table 2: Parameter significance of the SCE-UA algorithm. ANOVA results.

	EVALS		**OF**	
KSTOP	0.000	***	0.011	**
PCENTO	0.097	*	0.767	
NGS	0.000	***	0.000	***
ISEED	0.331		0.003	***

Statistical significance displayed in Table 2 shows how the parameters affect in the obtaining process of optimal solutions. KSTOP and NGS are the two parameters most significant, therefore if these parameters are modified the EVALS and OF value will be changed. Similarly, ISEED is statistically significant in OF value. However, the analysis indicates that the variation of PCENTO does not influence much as the previous ones. In contrast to the foregoing analysis (section 3.1), ISEED does not affect to EVALS, maybe due to the ANOVA performed here ignores the interaction between parameters.

In the Scatter Search algorithm, three parameters were analysed, each affecting EVALS in some way and thus affecting the computation time. Increasing the knowledge about this algorithm, the trials that have been carried out have demonstrated that the algorithm is not efficient for higher SIZEPOP values (more than 20 solutions) because a high EVLAS is required, obtaining similar results as when lower population sizes are used (10 or fewer solutions).

The REFSET parameter, for which the size is lower than SIZEPOP, is quite influential in optimised solutions. Considering SIZEPOP values less than or equal to 10, it is observed that low values of REFSET are most appropriate because, for different SIZEPOP values, optimal solutions are reached with a lower EVALS than in the case of higher REFSET values (as an example, REFSET=5).

Finally, for ITER values near 10 but lower than 20, the results obtained are reached with low EVALS values and optimal values for OF. This last parameter controls the stop condition of the algorithm. Given the results obtained with the Scatter Search and as Bhandari *et al.* (2012) have suggested, the statistical variance of the values of the best fitness should be considered as a termination criterion.

The same ANOVA analysis developed with SCE-UA algorithm has been done with Scatter Search algorithm. In this case, the sample used is equal to the analysis carried out in section 3.2.

Table 3: Parameter significance of the Scatter Search algorithm. ANOVA results.

	EVALS		OF	
REFSET	0.001	***	0.004	***
SIZEPOP	0.018	**	0.006	***
ITER	0.402		0.999	

Table 3 shows the statistical significance of Scatter Search parameters versus EVALS and OF value. REFSET and SIZEPOP are the most significant parameters that affect to the two dependent variables. This ANOVA analysis indicates how ITER is not significant unlike the descriptive analysis in section 3.2 (maybe for the same reason that ISEED in the SCE-UA statistical analysis).

It should be noted that in the analysis performed in sections 3.1 and 3.2, we have focused on the OF values and have looked for those results whereby OF was improved to the largest number of significant figures (up to the fourth decimal). Nevertheless, those OF values are related to the supply of demand 2, as seen in section 3. If we take 0.538 and 0.5389 as an example of OF values, the annual supply for demand 2 is 77.472 Mm^3/year and 77.6016 Mm^3/year, respectively. It can be observed that the difference is not very significant. This fact can be even more important in greater assignment demands, or in other problems with more complex OF, and depends on more variables.

Given this statement and considering the results of this analysis, it can be said that all the results are within the optimal range. This does not underestimate the analysis because these differences in the OF can be important in other problems, and, moreover, the conclusions obtained regarding the convergence/termination criteria of the algorithm and EVALS used in analysis are valid for any problem.

Comparing the results of the SCE-UA and the Scatter Search, the latter typically uses a higher EVALS than the former. Moreover, the SCE-UA obtains more optimal values of OF (inside the range considered to be optimal); nevertheless, the Scatter Search approach makes it flexible and able to provide excellent quality solutions, even when there are fewer parameters to vary for the global optimisation. Both algorithms allow the user to obtain optimal ORs combined with network flow SIMGES, noting that the SCE-UA is more efficient. Therefore, decision-makers could rely on on both algorithms to determine the best management for the WRS.

4. Application real case: Tirso-Flumendosa-Campidano

This section has three objectives: first, to demonstrate the usefulness of both EAs analysed in designing ORs for real WRSs; second, to determine which algorithm is better; and finally, to analyse the influence of decision-makers upon the optimisation pre-process and post-process (using an analysis of the results).

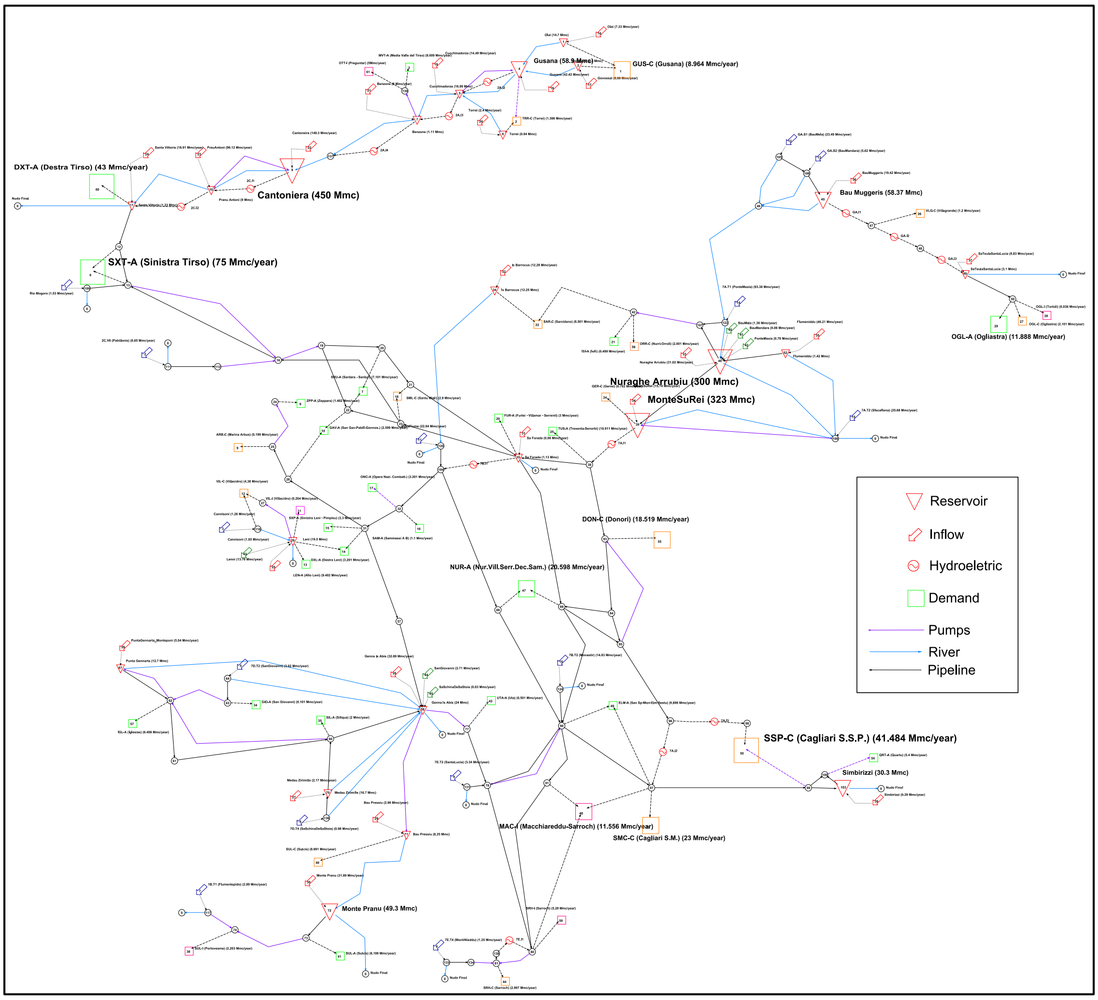


Figure 6: Schematic of Tirso-Flumendosa-Campidano system for SIMGES model.

The proposed methodology in section 2 is applied to the Tirso-Flumendosa-Campidano system located on the island of Sardinia (Italy). The system has a Mediterranean climate and is characterised by irregular distributions of water resources in time and space and by an irregular distribution of demand in time. All these factors suggest that the system can be considered one of the most complex systems to manage in the region. The average hydrological inflow of water resources to the system is approximately 750 hm^3/year. Furthermore, the total system demand is 383.25 hm^3/year. The water supply system is mainly characterised by the use of surface water that is stored and regulated by the reservoir. Groundwater is used only for small localised requirements. Figure 6 shows the complexity of the Tirso-Flumendosa-Campidano system, with 23 reservoirs, 14 diversion dams, 23 pumps and 44 demands. The main problem of the system is to carry water from areas with a high volume of resources to those with less availability. For this reason, the system has many pumping systems and pipelines that facilitate transport of the water to areas that need it, with a consequent economic cost. An important goal is to minimise the management cost of such pumping systems, while meeting as much of the demand as possible.
The Water Management Authority of Sardinia (ENAS) advised the building of the Tirso-Flumendosa-Campidano model. Once the simulation model of the management system was developed with SIMGES, the analysis was conducted, the most representative results of which are shown in Table 4. The results included in this table are the annual maximum deficit, the number of demands with a deficit and the total cost of operating the pumping system. These three aspects are considered in the OR optimisation process, given recommendations from ENAS. This demonstrates the participation of decision-makers in the optimisation pre-process because for ENAS, the priority is two-fold: to reduce the pumping costs and to reduce the demand deficits, which are both given the same level of importance.

Table 4: Results of the current management system for the case study.

a)

Number of demands with deficits	4
Average annual cost of pumping	3,675,330.24 €

b)

Demand	Maximum annual deficit
GIO-A	86 %
GUS-C	47.04 %
LEN-A	80.2 %
IGL-A	2.9 %

Four demands in the system suffer deficits (Table 4a), and one of them is an urban demand (GUS-C). The reason for this demand to suffer deficits is due to its location (in the upper sub-basins) and the lack of hydrological contributions in that area. These circumstances cause that demand to have two periods of several months in which it is not supplied with 100% of its water requirements. All other demands with deficits are agrarian demands. The average annual cost of pumping is 3,675,330.24 €, which is calculated using the volume pumped for each pumping system and their unit operating cost, all on an annual basis.
Departing from defined system management protocols, an optimisation problem is proposed to improve it, where the OF (Eq. 6) minimises the weighted sum of the maximum annual

deficit, number of demands with a deficit and pumping costs. The goal of the optimisation for this case study is to design ORs that obtain the least number of demands with a deficit and, at the same time, the lowest possible value for their maximum annual deficit. On the one hand, this approach is expected to affect the least number of users, considering user priority (urban demands have the highest priority). In contrast, when deficits occur, they are less damaging if they are distributed over a number of years than if significant deficits occur in any single year. Furthermore, the Tirso-Flumendosa-Campidano system has a complex infrastructure consisting of pipelines and pumping systems. The latter have a strong influence on management due to the significant economic costs of pumping. Because of this, the lowest pumping rate is also required to reduce the economic costs of higher operating rates for this pumping system. The problem with these two goals is that typically, in this type of system, the reduction in supply deficit for demands implies an increase in net pumping and, hence, the WRS operating cost. Therefore, the defined OF tries to minimise both quantities for optimal management.

$$OF = \left(0.3 * NDCD * C_{ND} + 0.2 * \frac{\sum DMA}{NDCD} * C_{DMA}\right) + 0.5 * \sum CB * C_{CB} \qquad (Eq.\ 6)$$

NDCD is the number of deficit demands, and C_{ND} is a coefficient that makes the term NDCD * C_{ND} be between 0 and 1. However, it also takes into account the type of deficit demands. In the case where more than one urban demand suffers a deficit (Eq. 7), the term NDCD * C_{ND} has a value of 1000. This implies that any solution where more than one urban demand suffers a deficit is not acceptable. DMA is the maximum annual deficit of each demand, and C_{DMA} is a similar coefficient to C_{ND}. In this case, it takes into account the vulnerability criteria (MARMA, 2008) used in Spain to verify the compliance of agrarian demands (Eq. 8-10). These criteria are based on the establishment of maximum limits for deficits that may occur over a given time period. Specifically, the time periods considered are 1, 2 and 10 years, and the threshold compliance rates for these periods are 50%, 75%, and 100% of the annual demand, respectively. In this way, the supply to the demand is considered "satisfactory" as long as the maximum annual deficit of the simulated series is less than 50% of the annual demand, the maximum deficit of two consecutive years is less than 75% of the annual demand, and the maximum deficit of 10 consecutive years is less than 100% of the annual demand. The last term of Eq. 3 takes into account the economic costs of the pumping systems (CB). The C_{CB} term is another coefficient that normalises the term CB * C_{CB}, and only for cases where the pumping cost exceeds a certain value (considered to be the upper limit) (Eq. 11); this term takes a value of 1000, designating any solutions above this upper cost limit to be unfeasible. Final values of OF will be between 0 (best solutions) and 1 (worse solutions), but as explained before, it can also take the value of 1000, indicating undesirable solutions.

Restrictions:

$$Deficit\ in\ Urban\ Demands\ \leq\ 1 \quad (Eq.\ 7)$$
$$Maximum\ 1\ Year\ Deficit\ (\%) < 50\%\ Annual\ Demand\ (Eq. 8)$$
$$Maximum\ 2\ Years\ Deficit\ (\%) < 75\%\ Annual\ Demand\ (Eq. 9)$$
$$Maximum\ 10\ Years\ Deficit\ (\%) < 100\%\ Annual\ Demand\ (Eq. 10)$$
$$Maximum\ Pumping\ Cost\ (€) < 5.000.000€\ (Eq. 11)$$

The OR for this real case is defined by six parameters, which represent the thresholds of different reservoirs of the system. These parameters are considered by the experience of the decision makers in the WRS. Based on these thresholds, the supply demands are restricted to a greater or lesser level and, at the same time, this affect to the volume pumped.

Optimisation has been carried out with both EAs previously described, the SCE-UA and the Scatter Search. The combination of parameters used in this real case reflects the best option considered in section 3. In the case of SCE-UA algorithm the OPT number is 20 and for the Scatter Search algorithm OPT number is 24. The results obtained, by using these parameters for each algorithm, are described below. To be able to compare these results with the current management of the system results, a value of 0.626 is obtained by evaluating the OF (Eq. 6).

For each EA, a figure with all the ORs analysed is displayed, showing the number of demands with a deficit (x-axis) and the average annual cost of pumping (y-axis). A decision-maker using this methodology can select between alternatives for what they consider to be the most desirable for the interests of the system in the post-process. For example, in this case, the decision-maker may choose an alternative with a greater number of demands with deficits, but with a lower net pump flow rate and thus lower pumping costs. These figures do not show the maximum annual deficits of demands with deficits because in most solutions, they remain constant. Nevertheless, in other cases, these figures alone would not be sufficient because they do not show all aspects of the WRS management needed for making objective decisions. For those cases, a collection of figures can be created to show all important aspects and relate different solutions across the figures using a colour code (Lerma *et al.*, 2014).

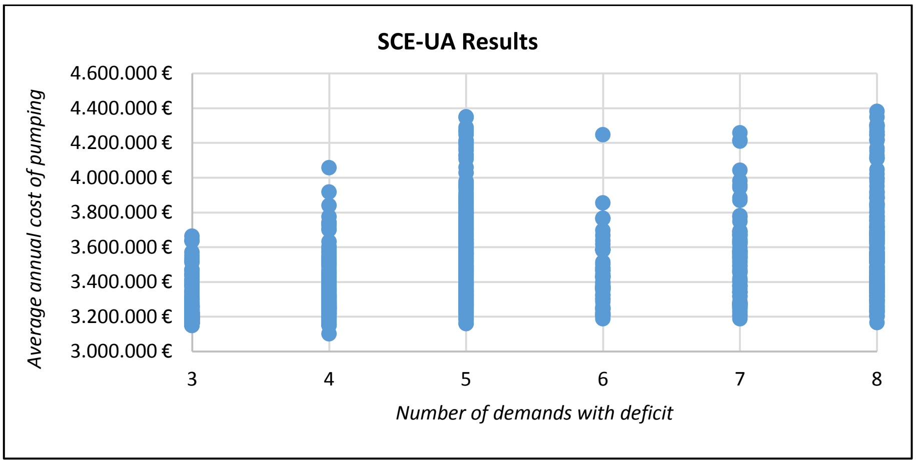


Figure 7: Obtained results using the SCE-UA algorithm.

The optimisation performed with the SCE-UA algorithm employed 1594 iterations to complete the process. The best value for the OF is 0.570, with an average annual pumping cost of 3,161,191.56 € and a total number of three demands with a water deficit. As shown in Figure 7 (which shows the results of all iterations), this is the solution with the fewest number of demands having a deficit and the lowest average annual cost of pumping; simultaneously, there is a significant reduction in the average annual cost of pumping, from 3,675,330.24 € to 3,161,191.56 €, a decrease of approximately half a million euros.

Alternatively, 3989 evaluations of OF were made using the Scatter Search algorithm (Figure 8), and the optimal solution obtained is one with three demands having a deficit and having an average annual cost of pumping of 3,251,280.22 €. The value of OF reached is 0.579.

The three demands that have deficits (in the best solution using both algorithms) show the same values of maximum annual deficit that are observed in the current management system (Table 4b).

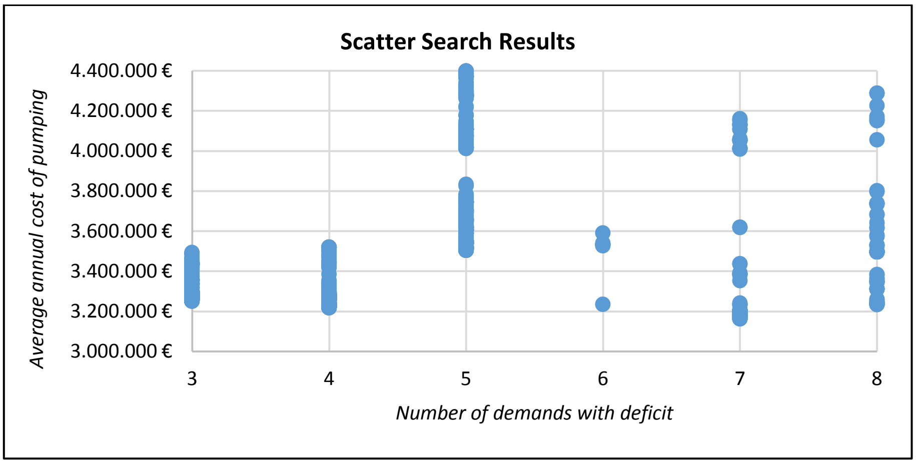


Figure 8: Obtained results using the Scatter Search algorithm.

At this point, we want to show the similarities and differences between the two EAs analysed. First, it can be seen that the number of iterations using the SCE-UA algorithm is smaller than that when using the Scatter Search algorithm, and without looking at any further aspect, one could say that the first algorithm is more efficient. Considering the OF and the results obtained, the best solution obtained by the algorithms is more optimal than the current management system, in terms of water supply deficits and pumping costs. Both algorithms are able to reduce the number of demands suffering a deficit from four to three. However, the SCE-UA obtains an average annual cost of pumping that is lower than that from the Scatter Search alternative, i.e., the SCE-UA obtains a better solution, but the Scatter Search nevertheless has fewer parameters, which makes it flexible and able to provide good solutions. Figure 8 shows that the solutions found by the Scatter Search algorithm are focused on specific values for the average annual cost of pumping, in contrast to the more or less homogeneous distribution that is shown in Figure 7 for the SCE-UA, i.e., there are ranges of the average annual cost of pumping that the Scatter Search does not analyse or does not provide any solutions for.

5. Conclusions

In this paper, two EAs have been assessed as optimisation tools to design optimal ORs in a WRS. Several aspects have been considered through analysis of each algorithm's parameters and a real case. The discussed aspects are aimed at a particular study of EAs: which is the best in real case applications, the convergence/termination criteria, and the influence of decision-makers in the optimisation process.

The parameter analysis allows us to better understand the behaviour of the SCE-UA and Scatter Search algorithms, detecting the most relevant parameters for the optimisation process. Simultaneously, their stop condition is also studied, through the parameters defined for that objective. The SCE-UA has three parameters for this purpose, while there is only one parameter for the Scatter Search, which gives SCE-UA more flexibility and therefore greater efficiency because it requires a lower number of OF evaluations in many cases. Regarding the remaining parameters, the NGS is quite important in the SCE-UA, in which neither values lower than 3 nor values higher than 8 are recommended to obtain optimal results in an efficient way. In the Scatter Search approach, to provide good solutions, parameters related to the population size and the Reference Set are most influential during the optimisation process.

When the EAs were applied to a real case study, other aspects related to the decision-makers were considered, apart from checking the methodology to design optimal OR using these algorithms. The participation of decision-makers in the optimisation pre-process is important in correctly addressing this problem, a correct representation of the results is needed for the post-process, and the decision-makers must have all the information necessary to make the best decisions that yield the most appropriate management protocols for the WRS.

Regarding the comparison of both algorithms, the SCE-UA needs fewer iterations to reach an optimal solution, and the solution obtained is typically better than the one obtained using the Scatter Search algorithm. Therefore, the conclusion is that the SCE-UA algorithm is a more efficient algorithm for realistic problems and obtains better, nearly globally optimised solutions when searching for ORs than does the Scatter Search, even if this second approach could be considered flexible and able to provide quality solutions in an expanded range of real-world applications.

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References

ADENSO-DÍAZ, B., GARCÍA-CARBAJAL, S. and LOZANO, S. An empirical investigation on parallelization strategies for Scatter Search. European Journal of Operational Research. Volume 169, Issue 2, 1 March 2006, Pages 490-507, ISSN 0377-2217, http://dx.doi.org/10.1016/j.ejor.2004.08.011.

AHMED, J.A. and SARMA, A.K. Genetic algorithm for optimal operating policy of a multipurpose reservoir. Water Resources Management 19, 2005, pp. 145–161.

AKTER, T. and SIMONOVIC, S.P. Modelling uncertainties in short-term reservoir operation using fuzzy sets and a genetic algorithm, Hydrological Science Journal, 49, 6, 2004, pp. 1079–81.

ANDREU, J., CAPILLA, J., and SANCHIS, E. Aquatool, a generalized decision support system for water resources planning and operational management, Journal of Hydrology, Vol. 177, pp. 269-291, 1996.

BHANDARI, D., MURTHY, C. A. and PAL, S. K. Variance as a stopping criterion for genetic algorithms with elitist model. Fundamenta Informaticae, Vol. 120, 2012, pp. 145-164.

BHASKAR, N. R. and WHITLACH JR., E. E.: Deriving of monthly reservoir release policies, Water Resources Research, 16, 6, 1980, pp. 987-993.

BOYLE, D. P., GUPTA, H. V. and SOROOSHIAN, S. Toward improved calibration of hydrological models: Combining the strengths of manual and automatic methods, Water Resources Research, 36(12), 3663 – 3674, 2000.

CAI, X., MCKINNEY D.C., and LASDON L.S. Solving nonlinear water management models using a combined genetic algorithm and linear programming approach, Advances in water Resources, 24, 2001, pp. 667-676.

CAMPOS, V., GLOVER, F., LAGUNA, M. and MARTÍ, R. An experimental evaluation of a scatter search for the linear ordering problem. Journal of Global Optimization 21, pp. 397–414, 2001.

CHJ (Júcar River Basin Organization). Hydrological Plan of Júcar Basin (in Spanish). Ministry of Environment. Spain, in BOE 191 11/aug/1998, 1998.

DOUGHERTY, D. E. and MARRYOTT, R. A. Optimal groundwater management 1. Simulated annealing. Water Resour. Res., 27(10), 1991, pp. 2493–2508.

DUAN, Q., SOROOSHIAN, S. and GUPTA, V. Effective and efficient global optimization for conceptual rainfall-runoff models. Water Resources Research, Vol. 28, No. 4, 1992, pp. 1015-1031.

DUAN Q., SOOROSHIAN S., GUPTA V.J. Optimal use of the SCE-UA global optimization method for calibrating watershed models. Journal of Hydrology, 158(3-4), 1994, 265-284.

ELFERCHICHI, A., GHARSALLAH, O., NOUIRI, I., LEBSI, F. and LAMADDALENA, N. The genetic algorithm approach for identifying the optimal operation of a multi-reservoirs on-demand irrigation system. Biosystems Engineering, 2009, pp. 334-344.

GLOVER, F. Heuristics for Integer Programming using surrogate constraints. Decision Sciences 8, 1977, pp. 156-166.

GOLDBERG, D. E. and KUO, C. H. Genetic algorithms in pipeline optimization. J. Comput. Civ. Eng. 1987.

GUO, Y.; WALTERS, G. A. and SAVIC, D. A. Optimal design of storm sewer networks: Past, present and future. Proc., 11th Int. Conf. on Urban Drainage (ICUD 2008), IWA Pub., London. 2008.

GUO, X., HU, T., WU, C., ZHANG, T., AND LV, Y. Multi-Objective Optimization of the Proposed Multi-Reservoir Operating Policy Using Improved NSPSO. Water Resources Management, 27(7), 2013, 2137-2153.

HOSSAIN, M. AND EL-SHAFIE, A. Evolutionary techniques versus swarm intelligences: application in reservoir release optimization. Neural Computing and Applications, 24(7-8), 2014, 1583-1594.

KUCZERA, G., Efficient subspace probabilistic parameter optimization for catchment models, Water Resources Research, 33(1), 177 – 185, 1997.

LERMA, N., PAREDES-ARQUIOLA, J., MOLINA, J. L. and ANDREU, J. Evolutionary network flow models for obtaining operation rules in multi-reservoir water systems. Journal of Hydroinformatics, 16.1, 2014, pp. 33-49 DOI:10.2166/hydro.2013.151.

LIBERATORE S. and SECHI G.M. Location and Calibration of Valves in Water Distribution Networks Using a Scatter-Search Meta-heuristic Approach. Water Resources Management. 23:1479–1495, 2009. DOI 10.1007/s11269-008-9337-6.

LOUCKS D. P. and SIGVALDASON O. T. Multiple reservoir operation in North America. In The Operation of Multiple Reservoir Systems, edited by Z. Kaczmarck and J. Kindler, IIASA Collab. Proc. Ser., CP-82-53, 1982, pp. 1–103.

LUCE, C. H., and CUNDY, T. W. Parameter identification for a runoff model for forest roads, Water Resources Research, 30(4), 1057 – 1069, 1994.

LUND, J., and FERREIRA, I. Operating rule optimization for Missouri River reservoir system. J. Water Resour. Plan. Manage, 122, 4, 1996, pp. 287-295.

MAIER H.R., KAPELAN Z., KASPRZYK J., KOLLAT J., MATOTT L.S., CUNHA M.C., DANDY G.C., GIBBS M.S., KEEDWELL E., MARCHI A., OSTFELD A., SAVIC D., SOLOMATINE D.P., VRUGT J.A., ZECCHIN A.C., MINSKER B.S., BARBOUR E.J., KUCZERA G., PASHA F., CASTELLETTI A., GIULIANI M. AND REED P.M. Evolutionary algorithms and other metaheuristics in water resources: Current status, research challenges and future directions, Environmental Modelling and Software, 62, 271-299, 2014, DOI: 10.1016/j.envsoft.2014.09.013.

MARMA (Spanish Ministry of Environment, Agriculture and Fishery), IPH (Guidelines for Basin Planning and Management) (in Spanish), in BOE 229 22/SEPT/2008, 2008.

MARTÍ, R. and LAGUNA, M. Scatter Search: Basic Design and Advanced Strategies. Revista Iberoamericana de Inteligencia Artificial. No.19. 2003. pp. 123-130.

MARTÍ, R. Scatter Search—Wellsprings and Challenges. European Journal of Operational Research. Volume 169, Issue 2, 1 March 2006, Pages 351-358, ISSN 0377-2217, http://dx.doi.org/10.1016/j.ejor.2004.08.003.

MIMAM (Spanish Ministry of Environment) Water in Spain. (English version), Centro de Publicaciones, Secretaría General Técnica, Ministerio de Medio Ambiente. Spain, 2004.

MOEINI R., AFSHAR A. and AFSHAR M.H. Fuzzy rule-based model for hydropower reservoirs operation, Int J Electr Power Energy Syst, 33, 2, 2010, pp. 171–178.

MOMTAHEN, S. and DARIANE, A. Direct Search Approaches Using Genetic Algorithms for Optimization of Water Reservoir Operating Policies. J. Water Resour. Plann. Manage. 133(3), 2007, 202-209.

MULETA, M. K. and NICKLOW, J. W. Decision support for watershed management using evolutionary algorithms. J. Water Resour. Plann. Manage. 131(1), 2005, pp. 35–44.

MURTHY, Z. V. P. and VENGAL, J. C. Optimization of a reverse osmosis system using genetic algorithm. Sep. Sci. Technol, 41(4), 2006, pp. 647–663.

NICKLOW, J., REED, P., SAVIC, D., DESSALEGNE, T., HARRELL, L., CHAN-HILTON, A., KARAMOUZ, M., MINSKER, B, OSTFELD, A., SINGH, A. and ZECHMAN. State of the Art for Genetic Algorithms and Beyond in water Resources Planning and Management. Journal of Water Resources Planning and Management 136(4), 412-432, 2009.

OLIVIERA R. and LOUCKS D.P. Operating rules for multireservoir systems, Water Resources Research, 33, 4, 1997, pp. 839-852.

SAVIC, D.A. and WALTERS, G.A. Genetic algorithms for least-cost design of water distribution networks. Journal of Water Resources Planning and Management, ASCE, Vol. 23, No. 2, pp. 67-77, 1997.

SCHEUERER, S. and WENDOLSKY, R. A scatter search heuristic for the capacitated clustering problem. European Journal of Operational Research. Volume 169, Issue 2, 1 March 2006, Pages 533-547, ISSN 0377-2217, http://dx.doi.org/10.1016/j.ejor.2004.08.014.

YOUNG, G. Finding reservoir operating rules, J. Hydraul. Div. Am. Soc. Civ. Eng., 93, 6, 1967, pp. 297-321.

ZIELINSKI, K., PETERS, D. and LAUR, R. Stopping criteria for single-objective optimization. Available on line at: http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.142.3511 (accessed December 10 2013), 2005.

Appendix 1. Test suite.

The next two tables contain the optimisation groups for SCE-UA and Scatter Search algorithms for the academic case. These tables mainly show the algorithm parameters, the evaluation number of the OF (EVALS) and the normalised OF value.

Table A1.1: Optimisations summary performed in SCE-UA algorithm analysis.

OPT	GROUP	KSTOP	PCENTO	NGS	ISEED	EVALS	OF
1	1	10	0.1	1	123456	172	0.5239
2	1	10	0.1	2	123456	476	0.5372
3	1	10	0.1	3	123456	419	0.5378
4	1	10	0.1	4	123456	441	0.5370
5	1	10	0.1	5	123456	1017	0.5382
6	1	10	0.1	6	123456	574	0.5378
7	1	10	0.1	7	123456	1531	0.5385
8	1	10	0.1	8	123456	1173	0.5379
9	1	10	0.1	9	123456	1493	0.5382
10	1	10	0.1	10	123456	1456	0.5382
11	1	10	0.1	15	123456	2893	0.5385
12	1	10	0.1	20	123456	3269	0.5383
13	2	2	0.1	7	123456	122	0.5333
14	2	5	0.1	7	123456	722	0.5375
15	2	15	0.1	7	123456	1841	0.5385
16	2	20	0.1	7	123456	2159	0.5385
17	3	10	0.2	7	123456	1043	0.5383
18	3	10	0.5	7	123456	978	0.5383
19	3	10	0.05	7	123456	1531	0.5385
20	4	10	0.1	7	967217	589	0.5389
21	4	10	0.1	7	583569	663	0.5369
22	4	10	0.1	7	657424	881	0.5378
23	5	10	0.1	7	967217	616	0.5389
24	5	10	0.1	7	967217	592	0.5389
25	5	10	0.1	7	123456	1043	0.5379
26	5	10	0.1	7	123456	1170	0.5381

Table A1.2: Summary of optimisations performed using Scatter Search algorithm analysis.

OPT	GROUP	REFSET	SIZEPOP	ITER	EVALS	OF
1	1	1	5	1	164	0
2	1	1	5	2	164	0
3	1	1	5	5	655	0.5331
4	1	1	5	10	1200	0.5367
5	1	1	5	20	2377	0.5367
6	1	1	5	40	4907	0.5367
7	1	1	5	50	6212	0.5367
8	1	2	5	1	164	0
9	1	2	5	5	795	0.5334

10	1	2	5	10	1578	0.5334
11	1	2	5	20	3222	0.5334
12	1	2	5	50	8430	0.5334
13	1	5	5	1	164	0
14	1	5	5	5	5784	0.5184
15	1	5	5	10	13487	0.5190
16	1	5	5	20	25444	0.5223
17	1	5	5	50	44444	0.5278
18	2	1	10	1	414	0.5331
19	2	1	10	2	414	0.5331
20	2	1	10	10	2377	0.5367
21	2	1	10	20	4907	0.5367
22	2	1	10	50	12018	0.5367
23	2	2	10	1	414	0.5331
24	2	2	10	5	1030	0.5380
25	2	2	10	10	2155	0.5380
26	2	2	10	20	4788	0.5380
27	2	2	10	50	12015	0.5380
28	2	5	10	1	414	0.5331
29	2	5	10	5	6184	0.5378
30	2	5	10	10	12717	0.5378
31	2	5	10	20	23996	0.5378
32	2	10	10	1	414	0.5331
33	2	10	10	5	28548	0.5380
34	2	10	10	10	40700	0.5380
35	3	10	50	1	2377	0.5367
36	3	10	50	5	30864	0.5379
37	3	10	50	10	64761	0.5379
38	4	10	100	1	4907	0.5367
39	4	10	100	5	30571	0.5385
40	4	10	100	10	64630	0.5385