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A model for solving the optimal water allocation problem in river basins with network flow programming when introducing non-linearities

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Abstract

The allocation of water resources between different users is a traditional problem in many river basins. The objective is to obtain the optimal resource distribution and the associated circulating flows through the system. Network flow programming is a common technique for solving this problem. This optimisation procedure has been used many times for developing applications for concrete water systems, as well as for developing complete decision support systems. As long as many aspects of a river basin are not purely linear, the study of non-linearities will also be of great importance in water resources systems optimisation. This paper presents a generalised model for solving the optimal allocation of water resources in schemes where the objectives are minimising the demand deficits, complying with the required flows in the river and storing water in reservoirs. Evaporation from reservoirs and returns from demands are considered, and an iterative methodology is followed to solve these two non-network constraints. The model was applied to the Duero River basin (Spain). Three different network flow algorithms (Out-of-Kilter, RELAX-IV and NETFLO) were used to solve the allocation problem. Certain convergence issues were detected during the iterative process. There is a need to relate the data from the studied systems with the convergence criterion to be able to find the convergence criterion which yields the best results possible without requiring a long calculation time.

Keywords *Network Flows, Optimisation Models, Water Allocation, Non-Linearities, Water Resources Management*

Introduction

The optimal management and operation of a water resources system involves allocating resources, developing stream flow regulation strategies and operating rules for reservoirs, and making real-time decisions within the guidelines of the operating rules (Wurbs 1993). The objectives of water resources system optimisation are to maximise benefits, minimise costs, and meet the various water demands, subject to the mass balance equation and other related constraints (Rani & Moreira 2010).

An optimisation problem consists of obtaining the best value (maximum or minimum) of a function formed by the decision variables for the system and the parameters representing the different weights of the decision variables. This function is called the objective function and is the heart of any optimisation technique (Wurbs 1993). However, an optimisation problem does not end with the objective function. In the case of water resources systems, the calculation of the best value for the control variables must comply with a series of restrictions such as the mass balance or maximum and minimum flow limitations.

The water allocation problem has the objective of finding the optimal distribution of the water between different users and uses within a river basin or a similar water resources system. This solution can be used later to solve problems such as drought management, defining the operating rules and environmental flows, and conflict resolution. Many Decision Support Systems for basin management are now focused on solving the water allocation problem (Andreu et al. 1996; Labadie et al. 2000; Wurbs 2005; Yates et al. 2005; Perera et al. 2005).

Labadie (2004) and Rani & Moreira (2010) reviewed the state-of-the-art regarding the optimisation techniques used for multi-reservoir systems, which represent the majority of water allocation problems. Both authors said that the most favoured technique for water allocation models has been linear programming. This technique has been used for optimising resources management of whole river basin schemes (Zoltay 2010), developing decision support systems for urban water supply areas (Yamout & El-Fadel 2005), and optimising irrigation water allocation in complex agricultural schemes (Reca et al. 2001a and 2001b). A reservoir system can be represented as a network of nodes and arcs, where nodes are the points of convergence or diversion and links represent reservoir releases, channel flows, carryover storage, and losses (Labadie 2004). Network flow programming is a computationally efficient form of linear programming and, as was shown by Kuczera (1989), is more suitable than linear programming for solving large multi-reservoir multi-period models. This technique has been used for the joint operation of large multi-reservoir systems (Chou et al. 2006), sizing of multiple reservoirs (Khaliquzzaman & Chander 1997), and elaboration of hydrological plans (MMA 2000). However, as is the case for linear programming, network flow algorithms require that both the objective function and the problem constraints be linear or linearisable. This means that certain important aspects of water resources systems management such as returns from demands, evaporation in reservoirs, or infiltration losses that have highly non-linear behaviours cannot be directly considered in the problem formulation. This problem has been dealt with in three ways: (1) the use of generalised network algorithms to handle networks with gains where arc flows may be adjusted with coefficients other than -1, 0 or +1, (Harou et al. 2010, Sun et al. 1995 and Hsu & Cheng 2002); (2) the successive solution of pure network problems with adjustment of the arc parameters until the results converge to the solution (Fredericks et al 1998); and (3) the use of equal flow algorithms to transfer equal or proportional flows in different arcs of the network as in Manca et al (2010).

This article presents a generalised optimisation model to solve the water allocation problem in water resources schemes with network flow programming. The model formulation takes into account evaporation from reservoirs and returns from demands. An iterative resolution process is presented to overcome the introduction of these two non-network constraints. The methodology is applied to the Duero River basin in Spain. Three well known network flow algorithms are used to solve the problem to investigate which gives the best performance and most efficiently finds the solution when used in an iterative optimisation process.

Tools and methods

Pure reservoir system simulation models reproduce the performance of a water resources system for given hydrological inflows and operating rules. These models are usually based on mass-balance accounting for obtaining the water volumes circulating through the system. Optimisation models determine the values for a set of decision variables that will maximise or minimise an objective function subject to constraints. Many network flow models can also be categorised as being "simulation" models in the sense that they are applied in the same manner as conventional simulation models. This means the problem can be formulated in a way that the operation rules of the system are reflected in the network characteristics, so the results will describe what will happen under those predetermined plans. However, network flow programming also allows the development of models with a more prescriptive orientation. Prescriptive models are those which determine the plan that should be adopted to best satisfy the decision criteria (Wurbs 1993). This prescriptive orientation of network flow programming is its most important feature for water resources systems optimisation. The advantage of using network flows for a prescriptive optimisation study is that many of the data are repeated every time interval, simplifying the definition of the network.

Generalised model formulation and network construction

The model presented in this paper optimises the monthly system management for a period of N years by minimising the following objective function.

$$\sum_{t=1}^{N\cdot 12}\left[\sum_{i=1}^{n_c}\sum_{j=1}^{n_i}\alpha_{i,j}\cdot d_{i,j,t}+\sum_{i=1}^{n_d}\sum_{j=1}^{n_{i'}}\beta_{i,j}\cdot d'_{i,j,t}\right]-\sum_{i=1}^{n_r}\delta_i\cdot V_{i,N\cdot 12} \qquad (1)$$

Where:

- N is the number of years in the optimisation period
- t is the number of month within each year
- n_c is the number of channels in the system, each with its ecological flow requirement divided into n_i levels
- n_d is the number of consumptive demands in the system, each of them divided into $n_{i'}$ demand levels
- n_r is the number of reservoirs in the system
- $\alpha_{i,j}$ is the cost assigned to the deficit $d_{i,j,t}$ of the level j of the ecological requirement in channel i in month t
- $\beta_{i,j}$ is the cost assigned to the deficit $d'_{i,j,t}$ of the level j of demand i in month t
- δ_i is the benefit assigned to keeping volume $V_{i,N\cdot 12}$ in reservoir i at the end of the optimisation period

This objective function is linear; the program minimises the weighted sum of the deficits in the ecological flows in channels and in the supply to consumptive demands and maximises the stored volume in reservoirs at the end of each optimisation period.

The weighting factors are defined as:

$$\alpha_{i,j} = K_\alpha - p_i \cdot K1 - j \cdot K2 \quad (2)$$

$$\beta_{i,j} = K_\beta - p'_i \cdot K3 - j \cdot K4 \quad (3)$$

$$\delta_j = 1 + n_r - p''_i \quad (4)$$

where K_α, K_β, K1, K2, K3, and K4 are user defined constants and p_i, p'_i, and p''_i are the assigned priorities for each ecological flow, demand and reservoir, respectively.

The optimisation of the previous objective function is subject to the habitual mass balance and flow bound constraints (Ahuja et al 1993).

The construction of the network flow is performed following the work of Kuczera (1993), Braga & Barbosa (2001) and Sechi & Zuddas (2007). The network is just a multiplication of the system scheme for the N·12 months comprising the optimisation period. The networks for a given month and the following month are linked by carryover arcs representing the stored volume in reservoirs. An example for a system with two reservoirs in series is given in figure 1.

Introducing non-linear aspects in the network definition.

Labadie (2004) described a gap between the theoretical developments of optimisation models for reservoir systems and real-world applications. One of the causes of this gap is the simplifications and approximations required to overcome hardware and software limitations. This means that many optimisation models do not completely represent or approximate the reality of the systems modelled, with a consequent lack of trust by operators and decision makers. In the case of network flow programming, the linear nature of both the objective function and the constraints makes it difficult to address aspects of the water resources systems that do not have a linear behaviour. This is the case for evaporation from reservoirs and return flows, which are two important aspects to be considered when considering a water allocation problem in a resource system. .

Evaporation is a system loss that can be significant in arid and semi-arid climate regions such as in Spain and other South European countries. Evaporation has a larger effect for larger water bodies. Evaporation is of particular importance in planning study models where usually only the main and larger reservoirs in the system are included. Not considering evaporation might yield inaccurate resource allocations with mistakenly increased demands. There are also the return flows from consumptive demands. These flows depend on the water use efficiency at the demand site. This means that, in systems with intensive irrigation demands, an important part of the water allocated to their supply will come back to the system somewhere downstream of the intake point.

Not accounting for return flows might therefore suggest a false resource deficiency for downstream uses.

Both evaporation from reservoirs and returns from consumptive demands are considered in the generalised model presented in this article. Also called non-network constraints, the problem with using these constraints is that the flows circulating through some arcs in the network are proportional to the flows circulating through different arcs. This proportionality problem is impossible to solve with a common minimum cost flow algorithm because these types of constraints cannot be considered in the calculation process. Different solutions have been considered in the literature for solving this network flow programming problem including generalised network flow algorithms (Sun 1995, Hsu & Cheng 2001, and Harou 2010), equal flow algorithms (Manca et al 2010), and successive solution of the pure network with arc parameters adjusted until convergence (Fredericks et al 1998, Ilich 1992).

Successive solution was used for handling these two aspects in the generalised model presented in this article. As seen in Labadie (2004), if few iterations are needed to achieve convergence, this process may be more efficient than the other two approaches because inclusion of non-linear conditions usually carries a computational price. The successive solution procedure also allows consideration of conditions where the associated flows do not have a proportional relation with other flows in the system, such as reservoir and channel seepage or aquifer connections.

A critical examination of the appropriateness of using iterations with network flow algorithms to approximate non-network constraints is provided by Ilich (2009). That paper concludes that any flow path restrictions that are updated through iterative calls of the network flow solver may fail to deliver reasonable solutions. However, the non-network constraint used as an example in the cited paper was outflow capacity related to reservoir storage. This can be considered an operation rule that is not the type of constraint that would be used in an optimisation model. The iterative process is crucial for obtaining the proper model results, and the definitions of the conditions determine how well the model works..

Each of the two considered non-linear aspects add extra arcs to the network. Evaporation adds one arc per month starting at the node representing the corresponding reservoir each month and ending at the balance node; its lower limit is zero and the upper limit will be changing through the iterative process. A very low flow cost value is given to the arc so that the maximum flow possible circulates through it and decreases the value of the objective function. Return flows will be considered as hydrological inflows. This means one arc per month will be created between the balance node and the return node in the system. Return flow arcs will not affect the objective function. Moreover, several demands can return to the same point in the system. The corresponding return flow values will be summed in these cases and no extra arcs will be created. The new arcs are also represented in the multi-period network shown in figure 1.

The flow diagram of the iterative process defined for the generalised model can be seen in figure 2 and works as follows:

- In the first iteration, both evaporation and returns are ignored by setting the upper capacity values of their corresponding arcs to zero and the pure network is solved normally.
- Second, with a first solution of the network, the theoretical evaporation and returns flows are calculated. These values correspond to the evaporation and return values that would occur under the flow conditions calculated in the previous step.
  The evaporation for reservoir *i* is calculated as:
  $$EV_{i,t} = EVR_{i,t} \cdot \frac{S_{i,t-1} + S_{i,t}}{2} \qquad (5)$$
  where $EVR_{i,t}$ is the monthly evaporation rate in month *t* and $S_{i,t-1}$ and $S_{i,t}$ are the reservoir surface at the beginning and at the end of the month, both calculated from the reservoir surface/volume curve.
  Return flow from demand *i* is calculated as:
  $$R_{i,t} = \alpha_i \cdot S_{i,t} \qquad (6)$$
  where α_i is the return fraction from demand *i*, and $S_{i,t}$ is the supply to demand *i* in month *t.*
- Third, the resulting values for evaporation and return flows are substituted as the upper limits of their corresponding arcs.
- Finally, the calculated evaporation and return values are compared with the values obtained in the previous iteration. If the difference for every arc is lower than the Convergence Error Value (CEV), the process will stop and the last calculated values will be considered correct. If the convergence criterion is not met on some arc, the program will do another iteration to solve the pure network.

The most critical aspect of this iterative process is the CEV. The CEV is initially set to 4 and represents a deviation of 0.04 flow units. This value was chosen during model development as it represented a fairly acceptable deviation value; it also worked well during the previous development of similar models. However, the value of the CEV affects the number of iterations as well as how “fine-tuned” the final results are. The relationships among this value, the number of iterations and the results are discussed below.

Solving the minimum cost flow problem

The network flow problem generated from a water resources scheme can be solved with a conventional linear programming algorithm. However, as has been stated before, the special structure of the network facilitates the use of more efficient algorithms which notably reduce the calculation time and allow studying larger problems with numerous variables and restrictions.

The generalised model presented in this paper allows for optimisation of a water resources scheme with three different, broadly known network flow algorithms: Out-of-

Kilter (Ford & Fulkerson 1962), NETFLO (Kennington & Helgason 1980), and RELAX-IV (Bersetkas & Tseng 1994). All three algorithms have been used previously to solve optimisation models for water resources systems (Chung et al. 1989; Kuczera 1993; Andreu et al. 1996; Khaliquzzaman & Chander 1997; Labadie et al 2000; Labadie 2006).

There are several references comparing the performance of the algorithms. Most of the authors (Bersetkas 1985; Bersetkas & Tseng 1988 and 1994; Kuczera 1993), agree about the superior performance of algorithms based on the relaxation method such as RELAX-IV and previous implementations. These algorithms usually perform faster by up to one order of magnitude than the other minimum cost flow problem algorithms.

All three algorithms are used in the case study below. This was not for studying the best execution time because that had already been studied. Although the time spent performing calculations is important, of more importance are the obtained results. Because each algorithm uses a different methodology to solve the minimum cost flow problem, the optimisation results might differ slightly from one algorithm to another. Thus, the performances of the algorithms are studied from a more “operative point of view”, checking whether aspects such as the distribution of storage in reservoirs (when more than one exists) make any of the algorithms more or less appropriate for the water allocation task. Moreover, the performance of the algorithms when working in an iterative manner is checked. As the iterative process changes arc capacities, this can be seen as a sensitivity analysis that will affect the number of iterations given a fixed CEV.

The Duero River case study

The Duero River basin is a trans-boundary system (figure 3). Of the 97,290 km^2 area of the basin, 81% (78,952 km^2) is in Spain and 19% (18,338 km^2) is in Portugal (CHD, 2008). The climate is continental with a strong Mediterranean character. The mean basin precipitation is approximately 625 mm/year, resulting in nearly 15,000 million m^3/year of available water in the river and aquifers.

Agriculture in the basin includes unirrigated (3.5 million ha) and irrigated (0.5 million ha) crops. Irrigation is the largest water consumer in the basin, using 80% (3,600 million m^3/yr) of the total volume of water consumed. The installed capacity of hydropower is 4,000 MW with an average production of 7,300 GWh/yr. The urban water demand in the basin is low, with most of the 2.3 million people living in small towns of 1,000 – 5,000. To comply with the objectives of supplying agricultural demands and producing energy, the water system has 75 large reservoirs with a total storage capacity of 7,500 million m^3. It is divided into 12 subsystems. These subsystems work independently, although complying with management conditions determined by basin policies.

The Duero River basin authority developed a scheme of the system for both simulation and optimisation purposes. For optimisation tasks, the scheme consists of 37 reservoirs (where evaporation is considered), 169 consumptive demands and 49 return points. The Duero River Basin Authority uses optimisation for different purposes, namely, developing new operation rules, estimating minimum shortages and maximum surpluses for demand increase studies, or studying the possible effects of climate change independently from actual management. Any of these purposes can be easily achieved with the presented model because its decision variables and constraints are oriented to these goals.

Each of optimisation purposes usually has a different modelling time horizon, For example, development of new operation rules requires optimisation over long time periods so regression can be applied afterwards, while shortages-surpluses studies are performed for a one or two year time horizon. The optimisation period depends very much on the system and the size of its reservoirs. A system with large reservoirs, usually of hyper annual operation, will need longer optimisation periods, while systems with small reservoirs that are only suited for fulfilling annual demands will use shorter periods. For the study presented in this paper optimisation time horizons of one, five, and ten years were used. . By doing this it could be shown how the model would perform for some of the different purposes explained before. One year would represent the most immediate operational management of the system; five years would be for short term planning, e.g. demands change; and ten year or longer periods would be used for long-term strategic planning and studying the impact of climate change.

Results and discussion

All the runs were performed using an Intel® Core™2 Duo CPU E7400 @ 2.80 GHz 2.80 GHz and 1.74 GB RAM. Table 1 shows a summary of the characteristics and results of the model runs performed for the Duero River system.

It was easy to predict based on the literature that Relax-IV would outperform the other two algorithms because it is approximately 30 times faster than Out-of-Kilter and approximately twice as fast as NETFLO. It was also easy to predict that larger networks would shower larger differences in execution times. However, table 1 shows that there are some small differences in the final objective function values and large differences in the number of iterations between the algorithms.

The value of the objective function in the first iteration, when there is no flow through arcs associated with nonlinearity, is the same for all three algorithms. The differences in the final value of the objective function are mainly due to the evaporation process and the high cost assigned to evaporation arcs to force that flow through them. The explanation of this effect is as follows. First, when the network is generated, the associated cost for water storage is the same for all reservoirs because the objective is to obtain the best operation of the system. Second, water resource systems are complex systems and most of the time the optimum value of the objective function will not correspond to a single point in the feasible solution space but to a hyper plane in which the objective function has the same value at all points. Finally, each of the algorithms has a different optimum search technique. Therefore, it is possible that, for the same complete flow distribution in the system, the individual storage in some reservoirs is different depending on the algorithm used. Because each reservoir has a different evaporation rate, the calculated evaporation may then also differ depending on the algorithm, which in turn affects the value of the objective function. Table 1 shows how the differences are more noticeable for longer optimisation periods and that the

NETFLO algorithm has larger differences with respect to the other two. This might be explained because Out-of-Kilter and Relax-IV have similar search methodologies that are different from NETFLO, with NETFLO being in the simplex method family, while the other two are in the dual ascent methods family.

Despite the differences in the number of iterations, only the Out-of-Kilter algorithm was able to converge to a solution in a small number of iterations. The other two algorithms were not able to reach convergence after more than 100 iterations. The objective function in these cases looped between two different values as shown in figure 4 for the case of one year optimisation. As has been stated previously, the convergence criterion is that the iterations must stop when the difference between the flow value at every non-linear arc and the new calculated flow value is lower than a certain value of CEV, as seen in figure 2. Depending on the system, the value set as a default CEV might be too low. It must also be taken into account that the optimum of the system will generally not be unique, leading the algorithm to continue yielding similar solutions that are never close enough to meet the convergence criterion, while the value of the objective function oscillates around a central value.

The effect on the results from modifying the convergence criterion was examined. The value of the CEV was gradually increased to determine whether the number of iterations was reduced and if that affected the final results. Figure 5 shows how increasing the value of the CEV reduces the number of iterations before convergence is reached with the RELAX-IV algorithm. This result is expected. What is more interesting is that the reduction in the number of iterations is not gradual but instead happens in steps. For values of CEV ranging from 4 to 8, the number of iterations is larger than 200. For CEV values of 9 and 10, the number of iterations performed is reduced to 157; and, for CEV values equal to 11 or higher, the algorithm only needs 3 iterations to reach convergence. The same procedure was performed with the NETFLO algorithm, and the number of iterations was reduced from more than 200 to only 3 for a CEV equal to 15.

Table 2 shows the results of one year optimisation period runs after completing the iterations required for different values of the CEV. As expected, the results for different CEV values do not differ very much from each other. These suggest that the size of the system will directly affect the convergence criteria and will permit defining less restrictive criteria for the larger the systems. This is a logical result because there is less concern about small variations in the numbers with large-scale systems while smaller systems will require more detailed results. The length of the optimisation period will also affect the choice of the convergence criteria.

A frequent modelling question is whether it is better to have very detailed, precise results that require a large amount of computation time, or to have a less detailed results that are more immediately available. The response to this question is that it depends on the situation. For a small system with a short time horizon, a more detailed and time-consuming analysis will be necessary, which means an algorithm that is less sensitive to small changes in the problem, e.g. Out-of-Kilter, should be used. Out-of-Kilter has been demonstrated to be a quick converging/less sensitive algorithm than the other two and thus it should be used when calculation time is not a constraint. . The similarity of the results for differing numbers of iterations and values of the convergence criteria suggests the possibility of simply stopping the iterative process after several cycles. By doing this, large systems with long optimisation periods could be solved in relatively short calculation times at the cost of having less fine-tuned results. It would be necessary to determine the point where the objective function starts oscillating and define a rule for stopping given the risk of not having reached pseudo-convergence.

Future research on the ideas suggested in this paper should involve trying the same process in several different systems so that similar patterns can be found and the general rules can be defined. The authors of this article are working on introducing new non-network constraints such as aquifers into the optimisation process. These additions should be included in a future convergence study of network flow algorithms.

Conclusions

Proper operation of a water resources system is crucial to maximising the benefits that can be obtained from the use of water. A good, proven efficient method to define the appropriate operating rules for a system is optimisation. The evident similarities between a water resources scheme and a network flow model make using this numerical method a fast and easy way for representing and calculating the flows through the system. However, the linear nature of this methodology is problematic when aspects of the water system possess a non-linear behaviour.

In this article, we have presented a network flow-based optimisation model for water resources schemes which considers two non-linear aspects by solving the network iteratively. The model was applied to the Duero River basin to show its performance at different optimisation time horizons. Three different network flow algorithms were used to solve the network problem and to study their performance when confronting an iterative process. As previous studies had already confirmed, RELAX-IV is actually the fastest algorithm for solving the single network problem. However, we detected that it has some problems finding a convergent solution when the network is slightly changed due to iterations. A less time efficient algorithm such as Out-of-Kilter proved more robust for this same task.

The convergence criteria defined for the iterative process strongly influences the number of iterations as well as the results. The modellers then have to decide whether to obtain less accurate results quickly or to wait longer to ensure convergence. An intermediate step that has been proposed is stopping the iterative process once it starts looping between two solutions. In the cases shown, the results did not differ much from each other. Nevertheless, each system studied in the future should be studied from the point of view of convergence. This means finding the convergence criterion which yields the best possible results without a long calculation time. We have given some ideas in this respect, but further investigation is needed to establish more concrete rules to relate the data of the system with the convergence criteria.

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Table 1 Optimization runs characteristics and results

Optimization Horizon (years)	1	5	10
Size of the network			
Arcs	17965	89101	178021
Nodes	6956	34220	68300
Non-Linear Arcs	1032	5160	10320
Average time per iteration (s)			
OOK	3.089	130.187	678.919
RLX-IV	0.184	5.221	22.571
NF	0.549	11.212	44.35
Number of Iterations			
OOK	3	7	7
RLX-IV	>100	>100	>100
NF	>100	>100	>100
Objective function			
OOK	$-7.204 \cdot 10^9$	$-3.555 \cdot 10^9$	$-7.126 \cdot 10^9$
RLX-IV	$-7.205 \cdot 10^9$	$-3.554 \cdot 10^9$	$-7.125 \cdot 10^9$
NF	$-7.205 \cdot 10^9$	$-3.562 \cdot 10^9$	$-7.139 \cdot 10^9$

Table 2 Total flow values for one year optimization period using different CEV values

	OOK (CEV=4)	RLX-IV (CEV=4)	RLX-IV (CEV=11)	NF (CEV=4)	NF (CEV=15)
Evaporation (Mm^3)	247.97	247.54	248.04	247.86	248.04
Return flows (Mm^3)	1104.26	1104.31	1104.29	1105.03	1105.03
Shortages (Mm^3)	627.66	627.66	627.66	627.63	627.63
Objective Function	$-7.204 \cdot 10^9$	$-7.205 \cdot 10^9$	$-7.198 \cdot 10^9$	$-7.205 \cdot 10^9$	$-7.202 \cdot 10^9$

Fig. 1 Example system of two reservoirs and two demands with its associated multiperiod network flow scheme

Drawn with Microsoft Visio

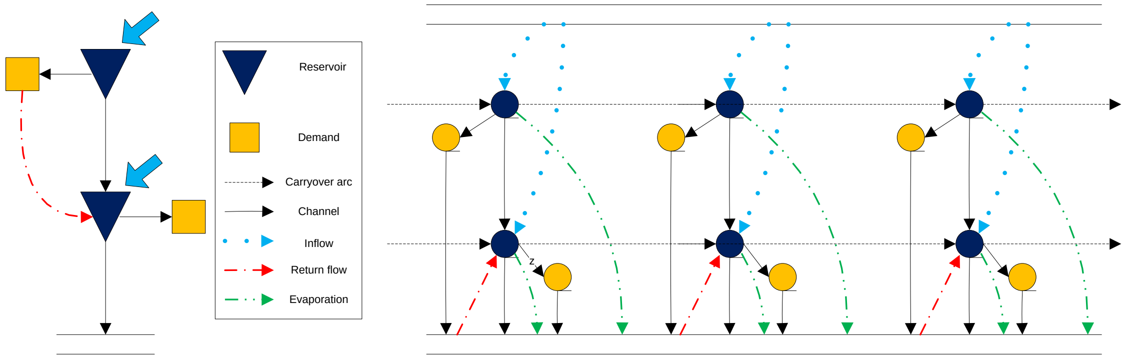

Fig. 2 Flow graph of the iterative process in the optimization model

Drawn with Inkscape

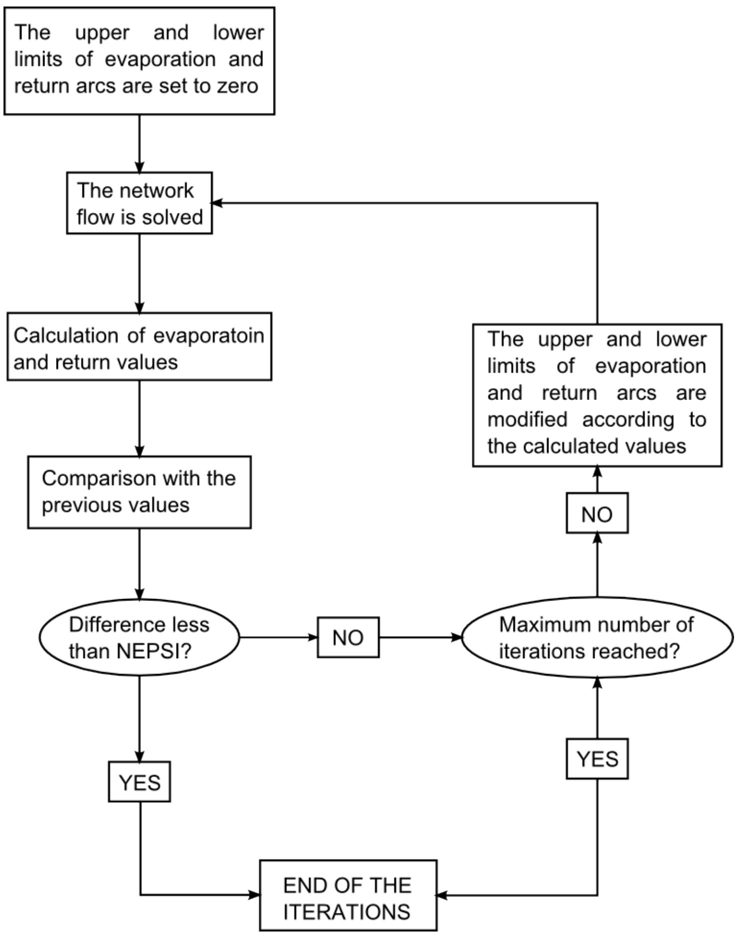

Fig. 3 River Duero basin territory

Provided by CHD, created with AQUATOOL DSS

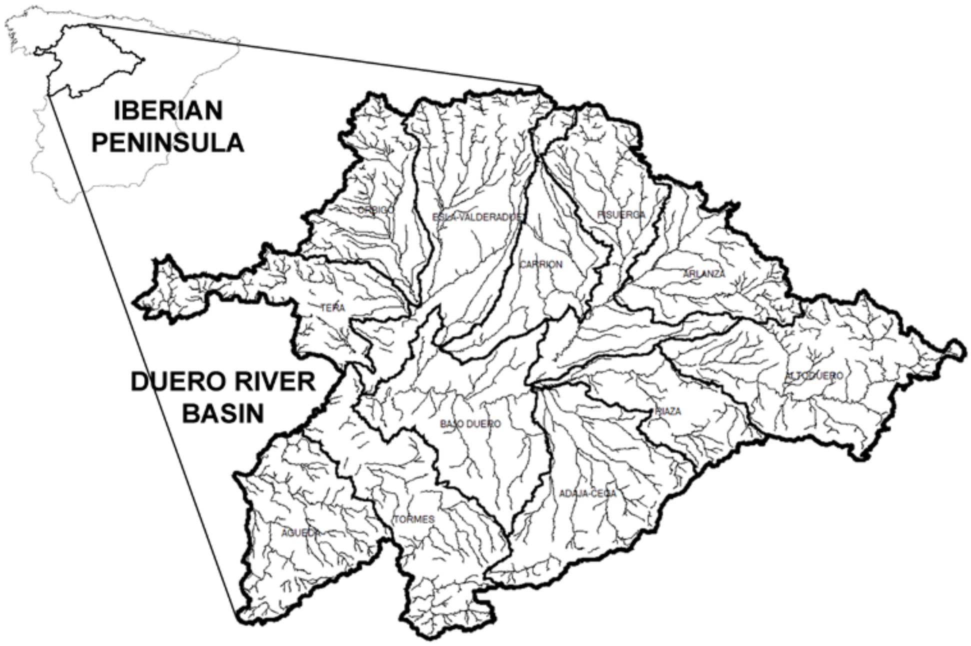

Fig. 4 Value of the objective function through iterations 2 to 10 for one year optimization period with CEV=4

Drawn with MS Office

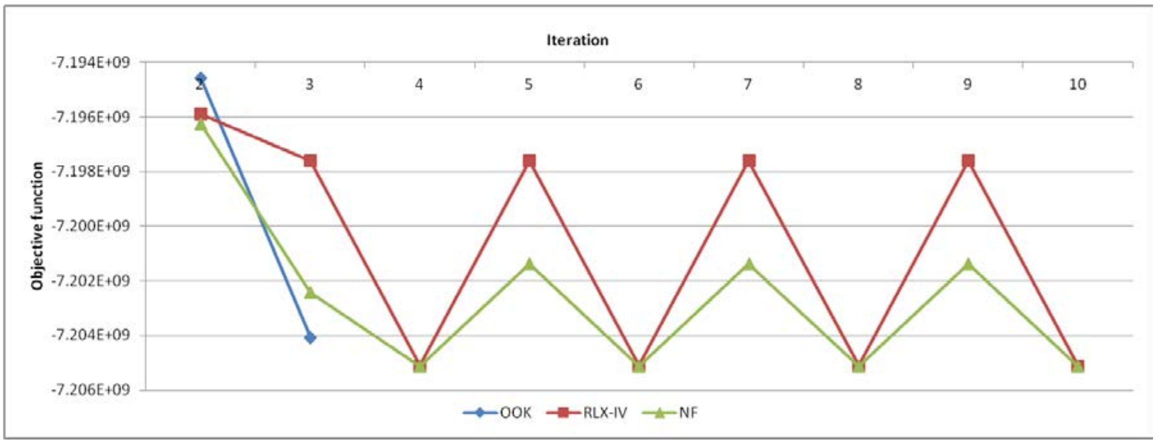

Fig. 5 Value of the convergence criterion and number of iterations needed to reach convergence.

Drawn with MS Office