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Integrating Historical Operating Decisions and Expert Criteria into a DSS for the Management of a Multireservoir System

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Abstract:

This paper presents a collaborative framework to couple historical records with expert knowledge and criteria in order to define a Decision Support System (DSS) to support the seasonal operation of the reservoirs of the Jucar river system. The framework relies on the co-development of a DSS tool that is able to explicitly reproduce the decision-making processes and criteria considered by the system operators. Fuzzy logic is used to derive the implicit operating rules followed by the managers based on historical decisions and expert knowledge obtained in the co-development process, combining both sources of information. Fuzzy regression is used to forecast future inflows based on the meteorological and hydrological variables considered by the system operators in their decisions on reservoir operation. The DSS was validated against historical records. The developed framework and tools offer the system operators a way to predefine a set of feasible *ex ante* management decisions, as well as to explore the consequences associated with any single choice. In contrast with other approaches, the fuzzy-based method used is able to embed inflow uncertainty and its effects in the definition of the decisions on the system operation. Furthermore, the method is flexible enough to be applied to other water resource systems.

Introduction

The operation of multireservoir systems requires complex decision-making processes, since they involve many variables, various (often conflicting) objectives and a considerable amount of uncertainty and risk (Oliveira and Loucks, 1997). System operators need to balance the decisions to address many objectives while complying with diverse constraints, agreements and traditions affecting water allocation and use (Lund and Guzman, 1999; Loucks and van Beek, 2005; Simonovic, 2009). Managers are therefore required to be experts in the water resource system they operate so they are able to recognize and match all the interests, pressures, constraints and available sources of information.

Mutireservoir systems management has been extensively studied in the literature, usually employing computer simulation or optimization models, or combinations of both (Yeh, 1985; Simonovic, 1992; Wurbs, 1993; Oliveira and Loucks, 1997; Labadie, 1997 and 2004; Rani and Moreira, 2010). The mathematical representation of system operation has been addressed by three different approaches in the literature: 1) using an optimization algorithm for real-time operation based on the system state and some forecasting tools; 2) developing *a priori* reservoir operating rules; and 3) building a representation of the implicit reservoir operating rules. The direct use of an optimization algorithm for real-time operation is marginal and only possible at short time horizons and in water resource systems in which the objective is unique and clearly defined, such as maximizing hydropower production or minimizing pumping costs (Teegavarapu and Simonovic, 2000; Castelletti et al., 2014; Caseri et al., 2015; Ficchi et al., 2016; Bauer-Gottwein et al., 2016). The fixed reservoir operating rules are usually derived through "rules of thumb" (Lund and Guzman, 1999) and a combination of optimization (to predefine optimal rules) and simulation models (for testing, evaluating and improving the rules) (Sigvaldason, 1976; Karamourz and Houck, 1982 and 1987; Karamouz et al., 1992; Andreu et al., 1996; Lerma et al., 2013; Aboutalebi et al., 2015).

Alternatively, estimating the operating rules implicitly followed by the system operators requires incorporating their expert knowledge into a mathematical representation of the system. Some existing methodologies for this purpose include: data mining (e.g., Bessler et al., 2003; Hejazi and Cai, 2011), which determines the variables considered by the system operators and fits a mathematical expression for them; fuzzy logic (Shrestha et al., 1996; Bai and Tamjis, 2007), which defines operating rules by extracting them from the historical records; and reinforcement learning (Lee and Labadie, 2007; Corani et al., 2009; Castelletti et al., 2010 and 2013, Giuliani et al., 2016), which optimizes the system operation by learning from historical observations

Despite the progress and the potential of mathematical models in reservoir operation, their use for real-time reservoir management is still limited (Labadie, 2004). On the contrary, the majority of the existing water resources systems are still managed based on fixed predefined rules, which specify the release for each reservoir based on the time of the year, state of the system and (sometimes) expected future hydrological conditions. One of the reasons for the use of these rules is that they are the result of a broader process, also including comprehensive negotiation and subsequent agreements on how to operate the system. Operating rules provide guidance to the system operators, but their judgement is still required in order to adapt them to the circumstances and the agreements with the users. In fact, system managers often deviate from these rules to adapt to specific conditions, objectives and constraints that may exist over time (Oliveira and Loucks, 1997). However, a joint modelling framework to reproduce the decision-making process is still lacking.

This paper combines the assessment of the implicit operating rules with the estimation of inflow projections in a single consistent framework resulting in a Decision Support System (DSS) for the seasonal operation of the Jucar River basin (Spain). To ensure a close reproduction of the real decision-making of the system operation, a continuous interaction between experts (system operators) and modellers is required. The system operators' criteria and historical records are used together to elicit the implicit operating rules, including how future inflows are forecasted in the system. Fuzzy logic is used to capture the experts' criteria, combine them with the historical records available and transform them into operating rules. Future inflows are estimated using fuzzy linear regression, integrating them with the elicited operating rules into a single DSS tool. This paper is structured as follows. In section 2 the methods used (fuzzy logic and fuzzy regression) are presented and their integration explained, together with the case study. In section

3 the Decision Support System for the Jucar River Basin operation is described and validated. The results obtained are presented in section 4. Finally, section 5 presents the conclusions of the research made.

Methods and material

Framework

The objective of the framework is to define a DSS able to reproduce the operating rules and decision-making processes used in the management of a water resource system. To adequately assess the decision-making procedures, system operators should be involved in the configuration and development of the DSS from the very beginning (Loucks and van Beek, 2005). The key idea is to treat the experts not only as future users of the tool, but as co-developers of a mathematical model whose goal is to help their decision-making processes, rather than to replace their judgment. Figure 1 shows the framework used in the development of the DSS system. It represents a continuous collaboration between the system operators (the experts) and the researchers or modellers from the preliminary stages to the development of the DSS tool.

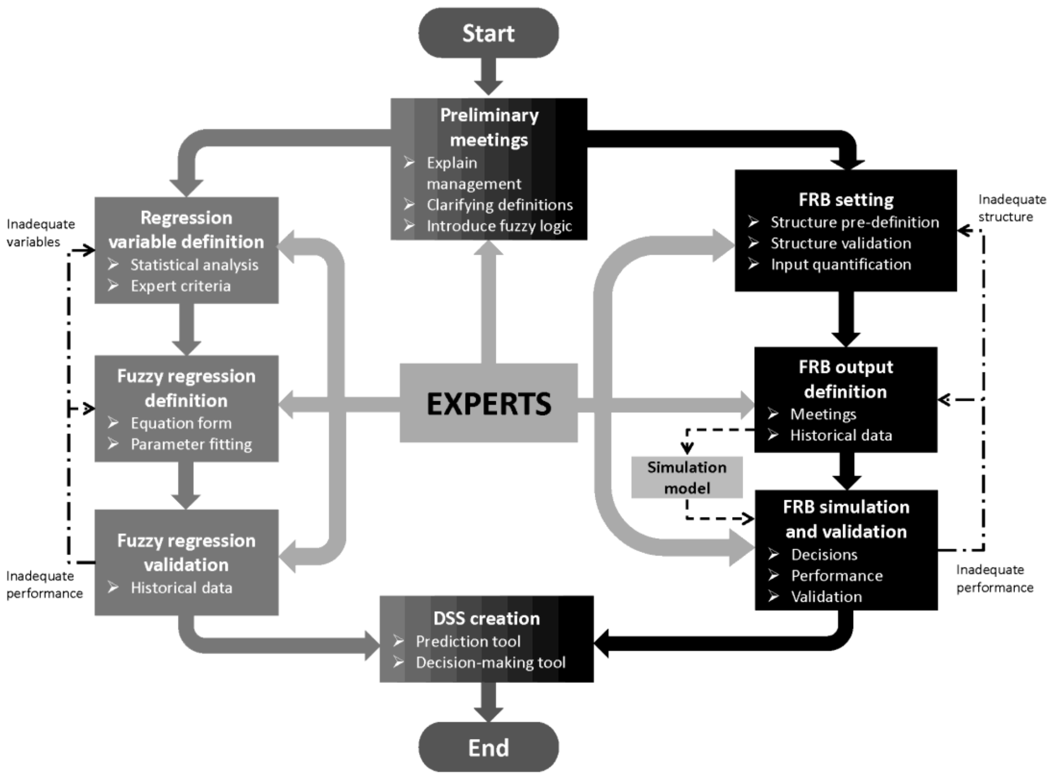

Figure 1. Collaborative expert-researcher framework

The framework consists of two parts: the definition of the operating rules (on the right) and the assessment of the variables (usually inflows) that need to be estimated in the decision-making processes (on the left). From the preliminary meetings, in which the system and its operation are discussed with the researchers or modellers, both parts are developed in parallel and then integrated into the DSS. Fuzzy rule-based systems (FRB) are used for the definition of the implicit operating rules. The main FRB features and outputs are decided through interactions with the stakeholders validated with the historical records to ensure that they reproduce the real operation of the system. Fuzzy linear regression is used to forecast the variables used in the decision-making process. The explanatory variables are selected by expert criteria, and then a regression equation is fitted to each one and properly validated against the historical data.

Fuzzy rule-based systems

Fuzzy logic (Zadeh, 1965; Mamdani, 1974) has been widely used to mathematically represent expert criteria. It offers an approach easily understood by the system operators who are not familiar with it and/or with complex mathematical procedures, due to its ability to link language and mathematics (Simonovic, 2009; Şen, 2010). It is also an efficient way to capture and treat uncertainty, being able to propagate its effect through all the mathematical processes considered (Simonovic, 2009). A fuzzy rule can be expressed as an IF-THEN sentence: *if input x is A and input y is B, then output z is C*. A and B are the rule premises and C is the rule consequence, all of them expressed using fuzzy numbers linked to linguistic descriptors such as “low”, “regular”, “acceptable” or “excessive”. That linguistic assimilation makes it more understandable (Şen, 2010). Under this framework, it is necessary to establish the degree in which a rule is followed, ranging between 0 (not followed) and 1 (definitely followed). Due to these features, fuzzy logic gets closer to reality, in which the true-or-false approach is hardly applicable (Şen, 2010). Besides, fuzzy logic model structures are based on human thinking, so they are easily understood by system operators (Dubrovin et al., 2002).

A fuzzy inference system or fuzzy rule-based system (FRB) consists of a set of fuzzy rules that are triggered simultaneously to link inputs and outputs (Şen, 2010). FRB systems have been applied to reproduce the operating rules of water resources systems and have been observed to perform well (Shrestha et al., 1996; Russell and Campbell, 1996; Panigrahi and Mujumdar, 2000; Dubrovin et al., 2002; Bai and Tamjis, 2007). They link key hydrological and water management variables (current storage, past inflows, current inflows, rainfall and so on) with water management decisions (target storage, release, deliveries to water demands, etc.). Figure 2 indicates the steps in the development of a FRB: 1) Preliminary analysis; 2) Input variables characterization; 3) Fuzzy rules definition; 4) Output determination based on historical data, mathematical algorithms and/or expert criteria; 5) Training; 6) Validation; and 7) Inference, composed of several sub-stages, which correspond to the usage of the FRB system created.

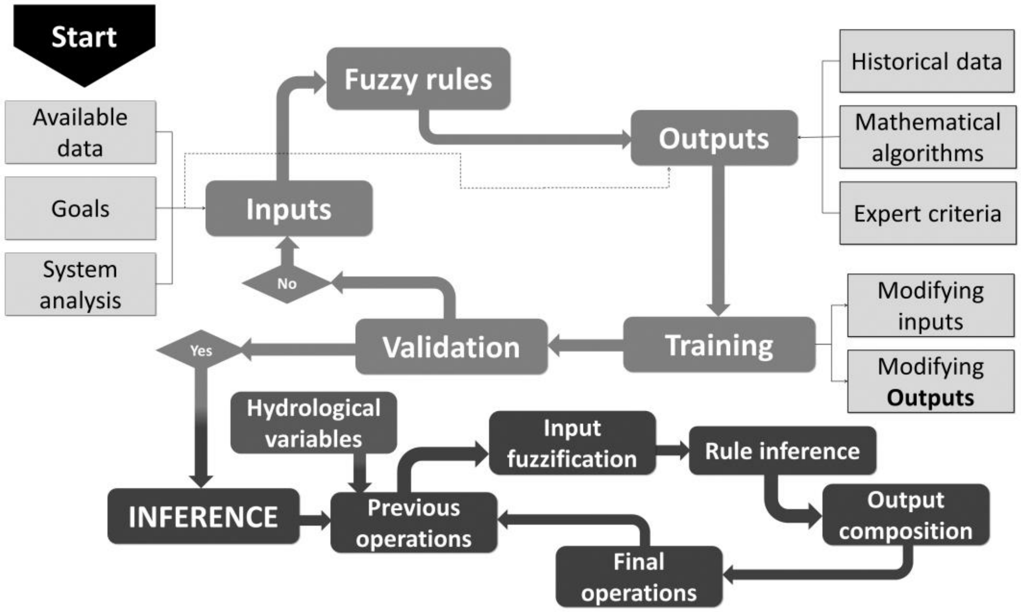

Figure 2. FRB system development and operation flowchart

Fuzzy regression for inflow forecasting

Fuzzy regression aims at describing relationships between system variables that are imprecise and/or with scarce or inaccurate data, illustrating the degree of uncertainty associated with regressive procedures (Bardossy et al., 1990; Simonovic, 2009). It simulates the dependency of an output variable with respect to one or several input (explanatory) variables. Fuzzy numbers are used as parameters under this approach (Bardossy et al., 1990) The advantage of fuzzy regression is that it is a conceptually simple tool capable of capturing the uncertainty associated with the regression using fuzzy numbers (Simonovic, 2009). It has been applied in hydrology with several goals, such as the evaluation of the uncertainty associated to stage-discharge curves (Shrestha and Simonovic, 2010); the derivation of operating rules, as with standard regression (Mousavi et al., 2007); and the calibration of fuzzy rainfall-runoff models (Özelkan and Duckstein, 2001).

Although any functional form can be used in fuzzy regression, the simplest way is to employ a fuzzy linear regression, as in Equation 1 (Simonovic, 2009).

$$\tilde{y} = \sum_i \tilde{c}_i x_i \qquad (1)$$

Where $\tilde{y}$ is the output variable, c_i the coefficients and x_i the input variables, which are the only ones that can take the form of non-fuzzy numbers. The resolution of the regression process requires determining the coefficients c_i via an optimization problem. These numbers are usually taken as L-R (left-right) fuzzy numbers (Bardossy et al., 1990) to reduce the complexity of the optimization problem. These coefficients must be selected to minimize a measure of the uncertainty or vagueness associated with the regression. This can be defined in several ways, or "vagueness criteria" (Bardossy et al., 1990). In this paper the authors consider the average vagueness, or average value of the support or width of all the fuzzy numbers c_i, labelled as S_c. Furthermore, the resulting regression must be able to properly represent the observed relationship between the variables. There are two different mechanisms to establish the "goodness of fit" depending on whether the historical records of the output variable are fuzzy or non-fuzzy (Bardossy et al., 1990). For the latter, considering j vectors of input and output variables $\{a_i, b\}_j$, it can be assumed that the fuzzy regression offers an adequate fit if, for each vector, the historical record b_j belongs to the output variable $\tilde{y}$ with a membership value $\mu_y(b_j)$ equal or greater than a fixed value h (Eq. 2).

$$Given \quad \tilde{y}_j = \sum_i \tilde{c}_i a_{i,j} \quad Then \quad \mu_{\tilde{y}}(b_j) \geq h \tag{2}$$

In which h ranges from 0 to 1. As a result, the optimization problem required to fit the fuzzy coefficients can be expressed as in Equation 3 (Simonovic, 2009).

$$\begin{aligned} &Minimize \quad S_c \\ &subject \quad to: \\ &\qquad\qquad \mu_{\tilde{y}}(b_j) \geq h \end{aligned} \tag{3}$$

Case study: Jucar River basin (Spain)

The Jucar river is one of the longest in Eastern Spain (Figure 3), flowing 497 km from the Iberian Mountains (Cuenca province), to the Mediterranean Sea (Valencia province), with a river basin area of 22,260 Km^2. Annual precipitation ranges between 309 mm and 717 mm, with an average of 473 mm. Its precipitation pattern is typically Mediterranean: high rainfall in autumn (especially in October), with a second peak in April-May; with very little precipitation during summer. Its mean total annual discharge is 1,548 Mm^3/year (CHJ, 2013), following the same pattern as rainfall. A significant percentage of the total river discharge (close to 70%) is provided by groundwater outflow via springs plus stream-aquifer interaction. The major regulation facilities (Figure 3) are the reservoirs of Alarcon (1,088 Mm^3 useful storage), Contreras (429 Mm^3) and Tous (369 Mm^3). There are 8 additional regulation facilities with useful storage greater than 1 Mm^3, mostly devoted to hydropower production (CHJ, 2013).

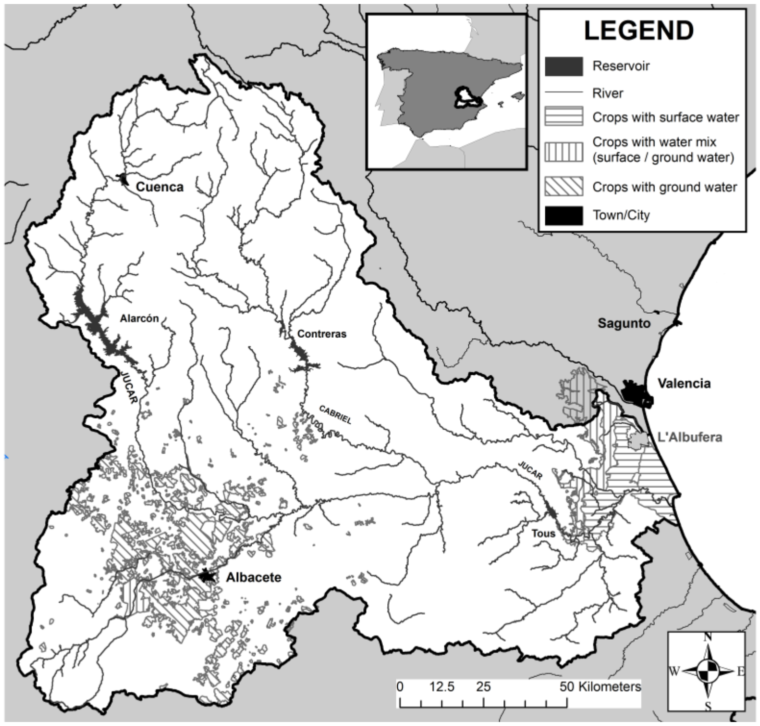

Figure 3: Jucar River basin location map

The annual mean consumptive demand in the Jucar River system is 1,505 Mm^3 for the 2009-2015 period (CHJ, 2013). By far the largest amount is for agricultural use (89%), followed by urban (9%) and industrial uses (2%). The most important urban districts supplied by the Jucar river correspond to the cities of Valencia, Albacete and Sagunto. Irrigated crops are concentrated in the lower basin, downstream of Tous, and in the middle basin, in the Mancha Oriental area. The latter is supplied from the Mancha Oriental aquifer, whose overdraft has caused a depletion of the Jucar river flows, with an inversion of the stream-aquifer interaction from gaining to losing river. In addition to these consumptive uses, the Jucar River basin holds 31 hydropower plants (with a total installed capacity of 1,272 MW). Furthermore, minimum environmental flows are set on 18 reaches located in the Jucar river and its tributaries (CHJ, 2013).

Jucar River system operating rules

The operation of the Jucar River system is subject to physical, environmental and legal constraints. In addition, traditional practices employed during its management must also be considered. The main physical constraints correspond to the reservoir, river and canal capacities. The environmental constraints are the minimum flows prescribed in certain river reaches, as well as the requirements of the Albufera wetland (a Ramsar protected wetland). The main legal constraint in the Jucar River system is the Alarcon Agreement, signed between the Spanish Ministry of the Environment (on behalf of the Jucar River Basin Management Authority, CHJ) and a users' association, *Unidad Sindical de Usuarios del Jucar* (USUJ), which gathers together the users with the most senior water rights owning the Alarcon reservoir. With this agreement, the USUJ transferred its management to the CHJ, thus enabling the joint operation of all the Jucar river facilities. In exchange, a rule curve was established for the operation of the Alarcon reservoir (CHJ, 2013). If its storage is below the curve, no surface deliveries can be arranged in the system except to the USUJ members, regardless of the storage in the rest of the system's reservoirs. Under this situation, any user who wants to employ surface water from the Jucar river should undergo negotiations with USUJ in order to reach an agreement concerning the amount of water to be allocated and the economic compensation that USUJ should receive in exchange of the transferred surface water, which must be substituted by groundwater.

Hydropower uses have, under the Spanish law and the Jucar River Basin Management Plan, less priority than urban and agricultural deliveries, so no release is made from any Jucar reservoir for the sole purpose of power generation. There are only three hydropower reservoirs with more than 1 Mm^3 of live storage, located immediately upstream of Tous, in series with each other and with Tous. Although the power company owning these reservoirs is able to balance their storages freely, it should release the same amount of water from the downstream dam as its upstream reservoir receives from Alarcon and Contreras. The rest of the hydropower reservoirs have little live storage, with no impact on the management of the system.

Shaped by the constraints and rules previously outlined, as well as by the traditions, the CHJ Operation Office (in Spanish, *Oficina de Explotación*) and the Jucar River Reservoir Releases Commission (in Spanish, *Comisión de Desembalse*) decide on the seasonal operation of the system. The latter establishes the amount of resources to be allocated during the irrigation season (May-September), while the Operation Office balances them among the Jucar reservoirs, monitors the process and controls the reservoir refill during the rest of the year (October-April). Outside the irrigation season, the minimum environmental flows and the inflows associated with the lower sub-basin are enough to satisfy the demands.

The criteria followed by the Operation Office when deciding how to balance the releases in the Jucar system consist of: 1) avoiding undesired spills from Tous; 2) increasing the flood pool to be kept empty in autumn; 3) not storing less than 40 Mm^3 in Tous, as it is the reservoir closest to the users, having it empty would make them think that their supplies were in danger of not being fulfilled; 4) avoiding falling below the rule curve; and 5) trying to balance the Alarcon and Contreras storage. With regard to hydropower, no releases are arranged for the exclusive goal of energy generation, but the power companies are allowed to turbine all the resource they can use from the Jucar river streams (respecting the environmental requirements) and the CHJ is committed to not use the resource stored in the hydropower reservoirs unless strictly necessary.

Decision Support System for the management of the Jucar river basin

In order to support the seasonal operation of the Jucar River basin, it is necessary to estimate how much water should be allocated to the agricultural districts during the irrigation season, as well as how much should be released from each reservoir (balancing the storage) to guarantee the planned deliveries. These predictions would help the CHJ Operation Office in their decision-making processes, since these assessments are currently made without the help of a DSS, which implies the absence of a homogeneous, systematic and robust decision framework in the process. The methods employed have been presented previously. A comprehensive description of all the stages required for its build-up is presented in the following sub-sections.

Model design based on experts' feedback

The major goal of the preliminary meetings with the experts was to obtain a clear picture of how the system is actually managed, to clarify the terms to be used in the process (avoiding potential misunderstandings), and to introduce fuzzy logic to the system operators in order to make them confident with the method. The management rules considered in the Jucar system were explained in the previous section. Prior to the irrigation season, the CHJ Operation Office predicts inflows using a deterministic forecast method based on the inflows observed in the last irrigation seasons and during the last months, precipitation projections for the irrigation season, rainfall during past irrigation seasons and expert knowledge. These projections are used to establish the amount of water initially expected to be delivered to the users during the irrigation season, which is discussed, modified if required and approved by the Reservoir Releases Commission. Then, the CHJ Operation Office determines how the water storage in Alarcon, Contreras and Tous should be balanced to guarantee the committed deliveries. During the irrigation season, the Operation Office establishes a release plan that is monitored, controlled, and modified if required, on a daily basis.

Considering the main system features explained by the system operators, a river network flow was established, incorporating the input and decision variables they use in the operational decisions (Figure 4). The storage at the three reservoirs (Alarcon, Contreras and Tous) and the inflow from the four sub-basins (Alarcon, Contreras, Middle and Lower) are the input variables for the Jucar river seasonal operation. The historical inflows were calculated through water balances as done by the Operation Office. Three urban demands and eight irrigation demands are included. The deliveries to the agricultural demands with groundwater are not affected by the decisions of the Operation Office, so they were not included in the model. Groundwater was also not explicitly modelled since its exploitation does not directly influence the decisions on the seasonal operation of the surface reservoirs. The influential stream-aquifer interaction between the Mancha-Oriental aquifer and the upper Jucar is already implicit in the middle sub-basin inflow time series. The only aquifer explicitly modelled is Hoces del Cabriel, exclusively to mathematically represent the return of Contreras seepage losses to the Jucar river (CHJ, 2013). Deliveries to the Cofrentes Nuclear Power Plant must be fully guaranteed and, consequently, it was included as a constraint rather than a demand. Hydropower plants were not considered since they are not taken into account in the decision of releases, nor do they have the possibility of causing an impact on the Jucar river seasonal management, as indicated previously. The environmental flows considered in the model are those that directly constraint the seasonal management: minimum releases from Alarcon and Contreras reservoirs and outflows to the sea. Additionally, some links were added to the model to account for undesired spills from Tous and excessive amounts of water to the sea, as the Operation Office seeks to minimize both terms.

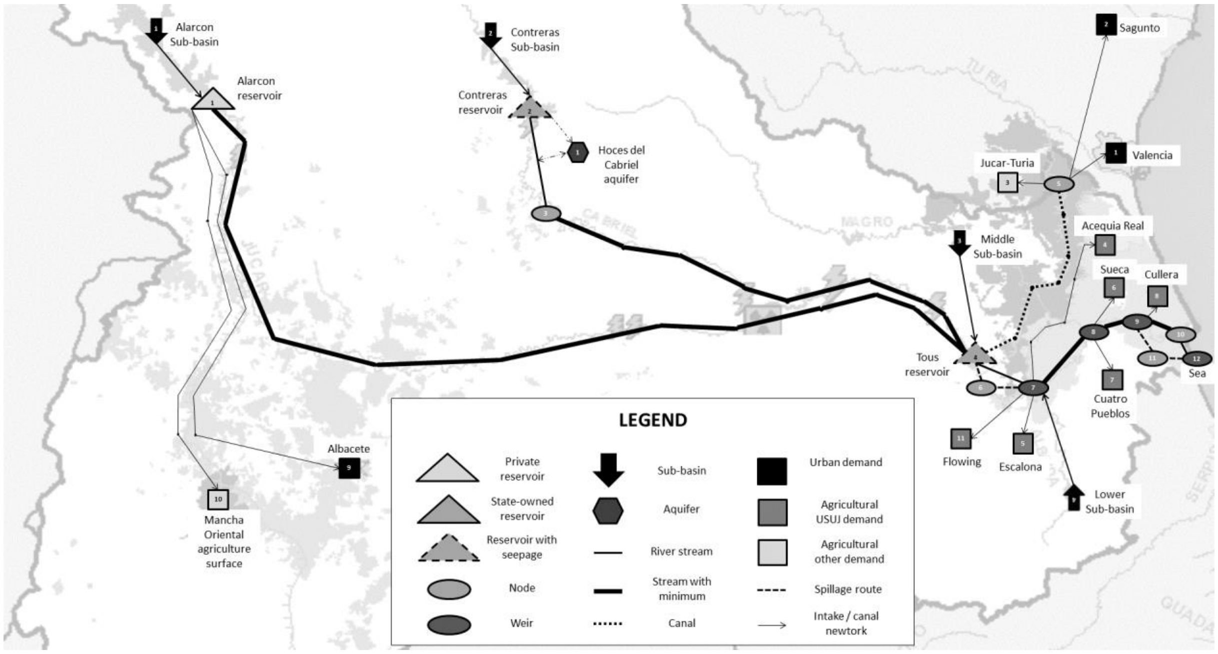

Figure 4: Schematic of the Jucar river system network

Delivery and release FRB models

In the Jucar river basin, the decision-making process involves two main milestones. First, the Reservoir Releases Commission decides, at the beginning of spring, how much water will be delivered to the users during the irrigation season (from May to September). After that, the reservoir operators (Operation Office) decide on how to balance the releases from the different reservoirs based on their storage and the predicted inflows to guarantee the planned deliveries. Accordingly, two FRB systems were built and linked to reproduce this decision-making process (Figure 5). On the one hand, the "Delivery FRB" aims to reproduce the decisions of the Reservoir Releases Commission, obtaining the releases from the downstream reservoir, Tous, based on the joint storage (Alarcon, Contreras and Tous storages) and the Lower sub-basin inflows, which together define the total amount of water available for downstream users. On the other hand, the "Release FRB·" represents the subsequent decision made by the Operation Office, establishing the percentage of the Tous releases that must be provided from each of the upstream reservoirs, Alarcon and Contreras. This decision is based on the storages in the three reservoirs and the forecasted Middle sub-basin inflows. The case of the deliveries to the city of Albacete and Mancha Oriental agricultural surface demands has some particularities: the deliveries of urban water to Albacete are always met and 33 Mm^3 per irrigation season are delivered to the irrigation districts in Mancha Oriental as long as the Alarcon Agreement allows that. Therefore, there is no need to incorporate both demands as outputs of the FRB system.

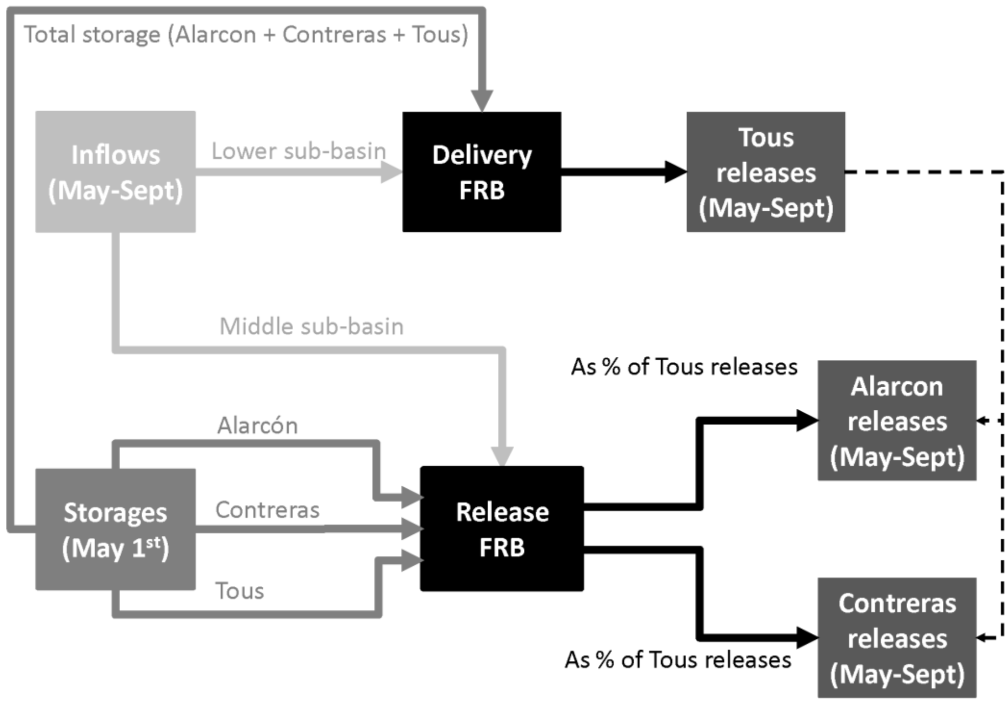

Figure 5. Modelling framework integrating the two FRB systems

The inputs of the Delivery FRB were characterized using five fuzzy numbers, combining together to form 25 rules. The output was defined as a non-fuzzy number. Moreover, the inputs of the Release FRB were characterized using three fuzzy numbers, combining together to form 81 rules. Their output variables were defined as non-fuzzy numbers. The input characterization in the latter FRB was kept as simple as possible to avoid an excessive number of rules. Both the inputs and the outputs refer to the whole irrigation season (between May and September) as a single time step, so the decisions made by it need to be further downscaled in order to establish a release calendar, a step currently carried out and supervised by the Operation Office.

Once the previous FRB structure was set, the proposed structure needs to be validated and the fuzzy inputs quantified. The formulation of the membership functions and rule bases was made based on both expert knowledge and historical data. Fuzzy membership estimation was based on the vertical method (Pedrycz et al., 2011) using two α-cuts (0 and 1), where each α-cut represents the interval formed by all the values that belong to a fuzzy number with a membership value equal or higher than α. The system operators addressed were asked about the intervals of the input variables that definitely belong or definitely do not belong to each fuzzy number. Then, a trapezoidal fuzzy number was set according to their answers (Figure 6).

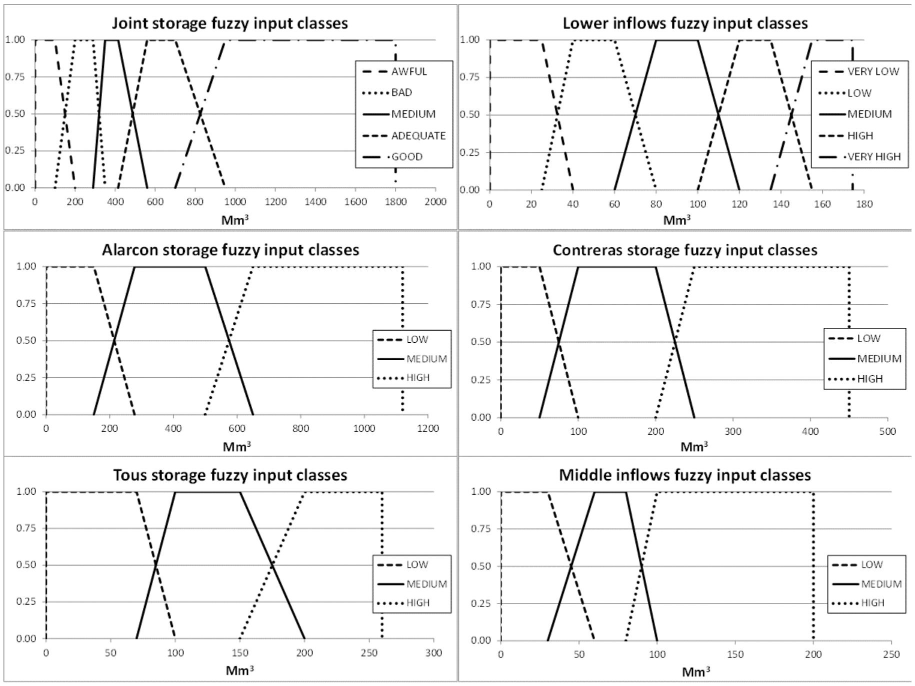

Figure 6. Fuzzy inputs for the FRB systems

Outputs defined for the FRB systems

Regarding the Delivery FRB, historical records for the 2003-2013 period were used to establish the output (Tous releases). A variant of the weighted-counting algorithm was employed (Shrestha et al., 1996). The rules whose output could not be determined by the historical data (because that situation did not happen within the period of the historical observations) were given an output based on the expert knowledge from the Operation Office. Historical records were used as the main drivers of the Delivery FRB, as not enough members of the Reservoir Releases Commission could be approached. With regard to the Release FRB, the outputs were given by the experts from the Operation Office. A workshop was organized, during which they were given a set of possible management situations (combinations between reservoir storages and Middle sub-basin inflows) and asked for their decisions under these circumstances. Each answer was used to obtain the outputs of the Release FRB.

FRB inference and validation

The FRB systems were validated to verify that their outcomes are in proper agreement with the current seasonal operating decisions (observed releases, streamflows and demand deliveries). In contrast with the procedures often followed in the development of operating rules, there is no training stage. This means that no objective function is used to modify the FRB systems, which are directly validated against historical records. The absence of training is due to the use of expert knowledge in the definition of the FRB systems and their outputs. Modifying them would imply losing the point of view of system operators, which is not desired. Therefore, only a validation stage was carried out; if the FRB systems were found to not be valid, then their definition process would need to be restarted (see Figure 1, Figure 2).

Their validation was made using a mathematical simulation algorithm, STIG, that takes into account the system network (depicted in Figure 4) for allocating water at each time step. The FRB systems were combined with the simulation algorithm. Each time stage, the inference procedure is applied for both FRB systems to obtain the target releases from the three reservoirs. These are then included in the simulation algorithm in the form of constraints that force its reservoir releases. The simulation model calculates then the streamflows and deliveries resulting from the target releases.

The resulting model was run with a monthly time step. Since we are dealing with reservoir seasonal operation for irrigation, the scheme presented is applicable to the irrigation season (May to October). Outside of the irrigation season the system operation is simpler: the only releases correspond to the minimum rates to fulfil the few winter irrigation demands plus the ecological flows and deliveries for urban water supply. In order to match the time scales between the model (monthly) and the FRB systems (seasonal), the seasonal decisions were disaggregated over time as follows. First, a curtailment coefficient to the releases from Tous was calculated as the division between the target release (obtained from the Delivery FRB) and the total downstream demand during the irrigation season. Then, this percentage was applied to each month to curtail the releases from Tous. The distribution of these monthly releases among the various downstream demands is made by the simulation model.

The model was validated for the 2003-2013 period, comparing its outputs with the observed reservoir storages and releases (Figure 7). The storages in Alarcon and Contreras are fairly reproduced by the model, given the high R-squared (0.97 and 0.96) and Nash-Sutcliffe efficiency (NSE, 0.92 and 0.96) coefficients. Despite not achieving the same performance, the goodness-of-fit for the Tous storage fit is adequate (R^2 = 0.72 and NSE = 0.68). Furthermore, the outflows from Tous seem to be well-fitted (R^2 = 0.81 and NSE = 0.78) to the historical observations. Consequently, it can be stated that the FRB systems are capable of correctly balancing the storage between the three reservoirs and reproducing the releases to the downstream demands from Tous.

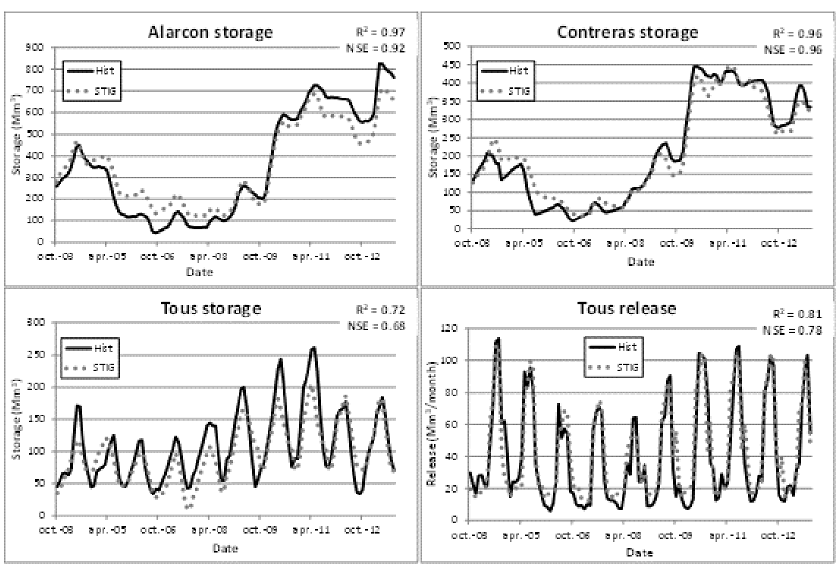

Figure 7. Validation for reservoir storages and releases

The validation process included other variables such as streamflow in different reaches and demand deliveries. Regarding river discharge, the R-squared coefficients ranged between 0.37 and 0.81, with an average value of 0.59. On the other hand, the validation for demand deliveries offered R-squared coefficients between 0.62 and 0.81, with an average value of 0.75. These results were discussed with the system operators. Since the model yielded adequate results compared with the historical records, both FRB systems were considered to be valid for their purpose, together providing a reliable representation of the actual operation of the Jucar River system.

Seasonal inflow forecasting using fuzzy linear regression

In order to build a Decision Support System (DSS) capable of making *ex ante* assessments of release decisions, it is necessary to establish a way to predict inflows during the irrigation season. To do so, an inflow forecast mechanism was developed for the Jucar river. A fuzzy linear regression equation was fitted to the inflow in each of the four sub-basins. Such a procedure is able to accommodate the experts' choice of variables in the estimation of future inflows, is conceptually simple and illustrates the uncertainty associated with the regression, since the output is a fuzzy number. In addition, it is able to provide suitable results even when available observations are scarce. In order to set up the regression equations for each sub-basin, the system operators pointed out different variables they consider when making inflow projections, such as rainfall in the past months (up to two years prior to the start of the irrigation season) and inflows in the past months. Then, a statistical correlation analysis between these variables and the inflows was used to select a final set of explanatory variables per sub-basin. The variables selected were:

- For the Alarcon sub-basin: rainfall during the previous months (October to April) and inflow during the previous months (October to April)
- For the Contreras sub-basin: rainfall during the previous months (October to April) and inflow during the previous months (October to April)
- For the Middle sub-basin: rainfall during the previous months (October to April) and inflow during the previous month (April)
- For the Lower sub-basin: rainfall during the previous months (October to April), inflow during the previous months (October to April) and inflow during the previous month (April)

Due to the scarcity of data (complete data sets were only available for the past 10 irrigation seasons) the number of independent variables was kept as low as possible. Consequently, spatial cross-correlations were not analysed (Table 1). Statistical correlation analysis showed that inflows in the upstream sub-basins (Alarcon and Contreras) have a stronger dependency on the explanatory variables (0.70 – 0.85 correlation coefficients), while the relationship between variables downstream is weaker (0.45 – 0.85 correlation coefficients). In fact, the Lower sub-basin linear regression was defined with three explanatory variables due to the weak correlations observed. The fuzzy coefficients of the regression were fitted using 8 years of observations (2003-2010), keeping the remaining two (2011-2012) to validate the regression. A membership threshold value (h) of 0.25 was considered since higher values would enlarge the width of the fuzzy outputs too greatly. Figure 8 shows the historical records (depicted using circular markers joined by dashed lines) versus the fuzzy results. As expected, the vagueness (grey tones) is higher in the regression of the lower sub-basin (with lower statistical correlations), while the others show similar vagueness levels. In any case, most observations fall into the region of non-pale grey tones, which makes the adjustment acceptable considering the scarce data.

Table 1. Correlation analysis results

Variable	**Sub-basin**	**Inflows May - Sept**			
		Alarcon	Contreras	Middle	Lower
Rainfall May–Sept	Alarcon	0.42	-	-	-
	Contreras	-	0.31	-	-
	Middle	-	-	0.07	-
	Lower	-	-	-	0.35
Inflows Oct–Apr	Alarcon	0.69	-	-	-
	Contreras	-	0.87	-	-
	Middle	-	-	0.80	-
	Lower	-	-	-	0.49
Rainfall Oct–Apr	Alarcon	0.68	-	-	-
	Contreras	-	0.85	-	-
	Middle	-	-	0.60	-
	Lower	-	-	-	0.53
Inflow April	Alarcon	0.65	-	-	-
	Contreras	-	0.89	-	-
	Middle	-	-	0.87	-
	Lower	-	-	-	0.47

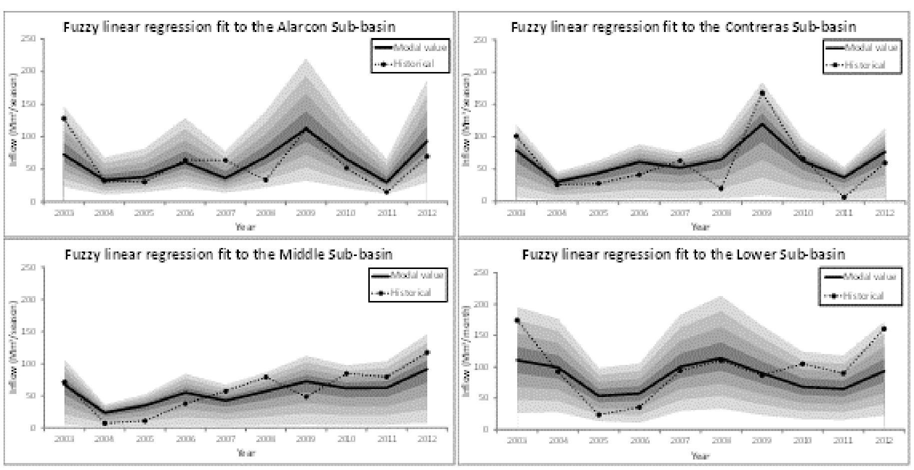

Figure 8. Results from the fuzzy linear regression of inflow by sub-basin; grey areas correspond to the output values: the darker the tone, the higher the membership value of the output

DSS tool and results

Once validated, the FRB systems and the fuzzy regression equations were combined in a single tool. The resulting DSS is able to make projections regarding future inflows, likely management decisions and their consequences. In order to be able to combine both procedures, the FRB systems were adapted to work with fuzzy inputs. The introduction of the inflows as fuzzy inputs was made using a fuzzy input decomposition scheme (Jones et al., 2009). This scheme consists in decomposing the fuzzy inputs into non-fuzzy values, using them as inputs for the FRB systems and building the fuzzy outputs via inverting the decomposition on the FRB output values. After calculating these outputs, their consequences (storages at the end of the irrigation season and water available for consumption downstream of Tous) were estimated using fuzzy arithmetic (for more details see Simonovic, 2009). End-of-season storages were calculated as the initial storage (non-fuzzy) plus the inflows (fuzzy) minus the outflows (fuzzy). Water available for usage in the lower Jucar was defined as the summation of the release from Tous (fuzzy) and the Lower sub-basin inflow (fuzzy).

The DSS was divided into two sub-tools to properly accommodate the two stages found in the seasonal operation of the Jucar river: the system state projections and the decisions regarding reservoir releases. The projections on the future possible system states in response to any possible decision is calculated by the predictive tool (Figure 9). Furthermore, the consequences associated with a specific decision are assessed by the decision-making tool (Figure 10). The first tool identifies a subset of likely decisions regarding the consequences that could be found for the entire possible decision set, while the latter determines the consequences of a particular decision.

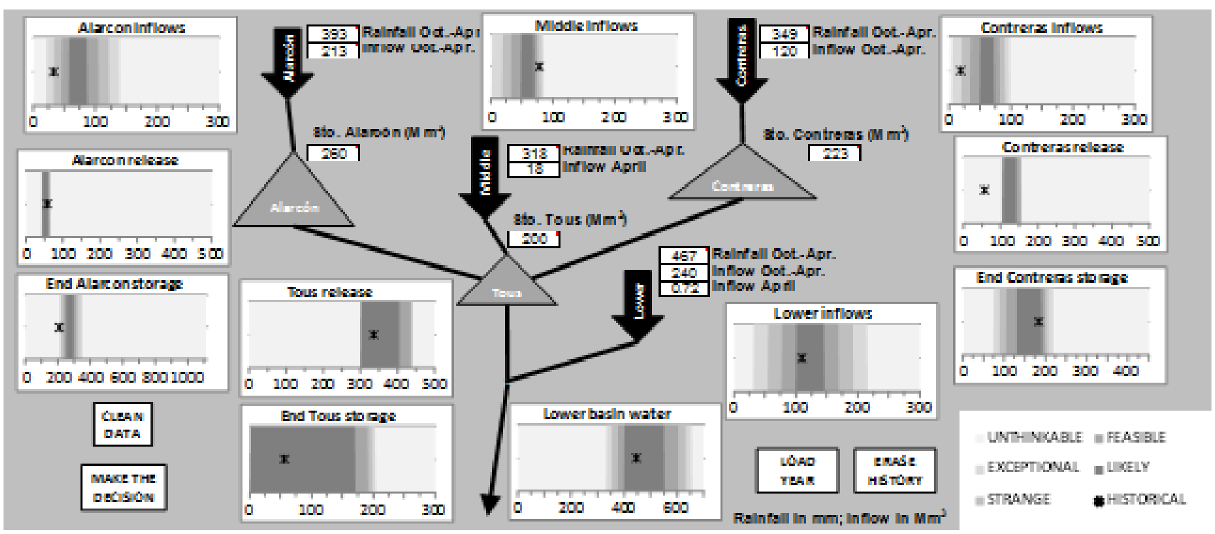

Figure 9. DSS predictive tool; includes predicted inflows, reservoir releases, end-of-period storages and water availability in the lower Jucar

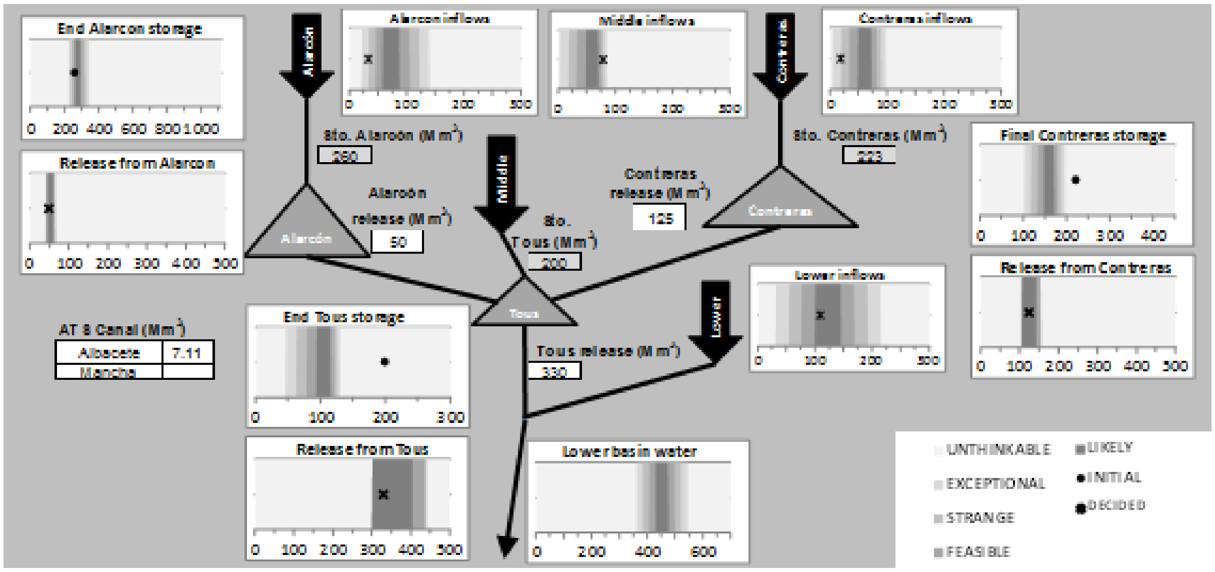

Figure 10. DSS decision-making tool; includes predicted inflows, reservoir releases, end-of-period storages and water availability in the lower Jucar

The usage of the DSS starts with the predictive tool, in order to locate possible release decisions in response to the previewed inflows. In that tool, the user introduces the initial system state (reservoir storages at the end of April) and the meteorological and hydrological variables for predicting inflows (past rainfall and inflows). The tool calculates fuzzy estimations of the future inflows and shows them to the user (Figure 9). Automatically, it computes likely reservoir releases inferring them from the FRB systems, obtains the end-of-season storages using fuzzy arithmetic and estimates the water availability in the lower Jucar via fuzzy arithmetic. Since all these outputs obtained are fuzzy, the user has an estimation of the uncertainty associated to the inflows and how it affects the release decisions and the final storages.

To facilitate the interpretation of the fuzzy numbers obtained by the predictive tool, a visual code attached to linguistic descriptors was used. These descriptors are "unthinkable" ($\mu=0$), "exceptional" ($0\leq\mu\leq0.25$), "strange" ($0.25\leq\mu\leq0.50$), "feasible" ($0.50\leq\mu\leq0.75$) and "likely" ($\mu\geq0.75$). They are the primary metrics for comparing release decisions, and locating and sorting the operating options by likelihood. Any *ex ante* decision falling within the "feasible" and "likely" zones would be in line with the expected inflows and the current system operating rules. Decisions inside the "exceptional" and "strange" areas would be initially inconsistent with the forecasted inflows and/or the current operating rules. Decisions falling in the "unthinkable" zone should not be considered at all, since they clearly depart from the expectations at the start of the irrigation season. Consequently, the user has an immediate estimation of which are the most likely decisions, being able to quickly rank them according to their acceptability. The usage of common-knowledge linguistic descriptors and visual codes facilitates that comparison, as well as making it easier to show it to stakeholders or decision-makers not familiar with the tool. Another advantage is that the tool screens all the possible values of the release decisions, so all the alternatives are analysed. Furthermore, the tool estimates the expected end-of-season storages and water availability downstream of Tous for any operating decision. Consequently, it allows the user to determine if any discretional decision or additional measure (like groundwater pumping) should be considered to save surface water or increase the downstream users' supply. As an example, if the water availability in the lower Jucar river offers low values within the "feasible" and "likely" intervals, then more water than initially indicated should be released from the reservoirs or complemented with groundwater pumping. Similarly, if the Tous reservoir presented lower storages within the previous intervals, then more water than preview should be released from upstream to prevent it from becoming empty.

Despite ranking any possible release decision according to its acceptability, the predictive tool does not pick any single one as the best. On the contrary, a set of promising alternatives is provided, so they can be used as the starting point for negotiation processes. Consequently, no additional metrics were employed to perform finer decision rankings. The decision-making tool (Figure 10) was included to facilitate the estimation of the consequences obtained by a single decision. In that tool, the user introduces a single decision (releases from Alarcon, Contreras and Tous, as well as water deliveries to Albacete and Mancha Oriental crops), and immediately finds out its likely consequences (end-of-season storages and water available downstream Tous). The decision-making tool also shows the inflow forecasts and the reservoir releases previously obtained by the predictive tool, in order to easily determine how the decision introduced was ranked by it. Although it would be expected that the decision made would be one that had obtained a good rank ("likely" or "feasible") through the predictive tool, any decision can be typed in, thus enabling any alternative to be explored. The decision-making tool implements the same fuzzy arithmetic operations as the predictive tool, but replacing the calculated releases by the values introduced by the user. In that way, the tool immediately shows the user the possible consequences of the proposed releases, ranked by their likeability, thus the impacts of the applied operating decisions can be quickly determined. If these are found to be inadequate, another decision can be typed in and its consequences are automatically shown by the tool.

Discussion and Conclusions

This paper presents a collaborative framework to couple historical records and expert knowledge/criteria in the definition of a Decision Support System (DSS) to support the Jucar river seasonal management. Fuzzy logic is used to estimate the operating rules implicitly followed by the Jucar River basin managers, employing fuzzy regression to forecast future inflows based on past meteorological and/or hydrological variables. The tool offers the experts a way to preview which decisions would be *a priori* adequate, as well as to estimate the likely consequences of any decision they want to examine.

Although the framework presented was designed for and applied in the Jucar River system, it can be extrapolated to any other basin. In this paper, the method is presented jointly with its application to the case study, as it was shaped and built in a continuous fashion during meetings with the Jucar River system managers. Developing such a continuous building mechanism is vital for the success of the tool, since new insights on how the system and its management work are gained during the process and thus incorporated in the final outcome.

As pointed out by the experts (system managers) during the process, the main reasons why they were satisfied with the resulting tool were: 1) it implements specific features and variables that system operators consider for the actual operation, 2) they were able to properly understand how the approach works despite the initial lack of familiarity with fuzzy logic, 3) the simple lay out and usage of the approach, and 4) that the approach does not select a single decision, but rather suggests a range of possible ones and their likely consequences. Fuzzy logic proved its suitability for being understood by people without a solid grounding in its theory, as well as being proper method of estimating implicit operating rules, which were encoded in its fuzzy rules defined by expert criteria and historical records of the decisions made.

Despite the potential of the approach and the good performance in its implementation in the case study, several weaknesses must be addressed. Firstly, the quality of the regression process was hindered by the lack of data availability. It is likely that regression could improve if new records were added. More specifically, new variables would be required to adequately capture the variability observed by the lower sub-basin regression, as well as in the others, in which there are several values that need to be explained by regarding variables not included in the equations. Besides this, the accuracy of the fuzzy rule-based systems could be improved by adding additional fuzzy rules in order to obtain a finer discretization of the fuzzy inputs, although this would make the process of incorporating the expert criteria harder because of the increase in fuzzy rules. With regard to this, Şen (2010) pointed out that using more than seven fuzzy numbers to characterize a variable would make it difficult for people to understand the FRB, as the meaning of the linguistic terms would be too similar to allow people to make a clear distinction between them.

Furthermore, the FRB systems and the fuzzy regression equations operate under the assumption that the inflows are uncorrelated, which does not correspond to the real behaviour. As a result, the uncertainty intervals provided by the DSS tool are higher than expected in real-life. Solving this issue would require more detailed FRB systems (more rules) and fuzzy regressions (more variables), something that needs additional data (fuzzy regression) or could make the process difficult to understand (FRB systems).

Regarding the DSS building process and its implementation in the Jucar River system, the following conclusions can be drawn:

- The collaborative process set was able to couple historical data and expert judgement, taking advantages of the synergies found between both data sources.
- Fuzzy logic was successful in establishing the implicit operating rules followed in the Jucar River system through combining historical records and expert criteria.
- The DSS created for making *a priori* assessments of the management decisions applied in the Jucar River system offers a quick and adequate way to help the decision-making process: experts are able to foresee possible decisions and to anticipate the possible consequences of these decisions.
- Although the uncertainty regarding future inflows is addressed by the tool, the quality of its estimation is hindered by the lack of data. In particular, the uncertainty band provided by the tool could be larger than the real one. Therefore, the inflow prediction mechanism should be re-assessed as soon as new data sets are available.
- Collaborative Decision Support Systems (DSS) such as the one developed in this paper are likely to have the best chance to be implemented in reality, since the experts who

should use them are directly involved in the process and thus feel confident with the resulting tool.

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