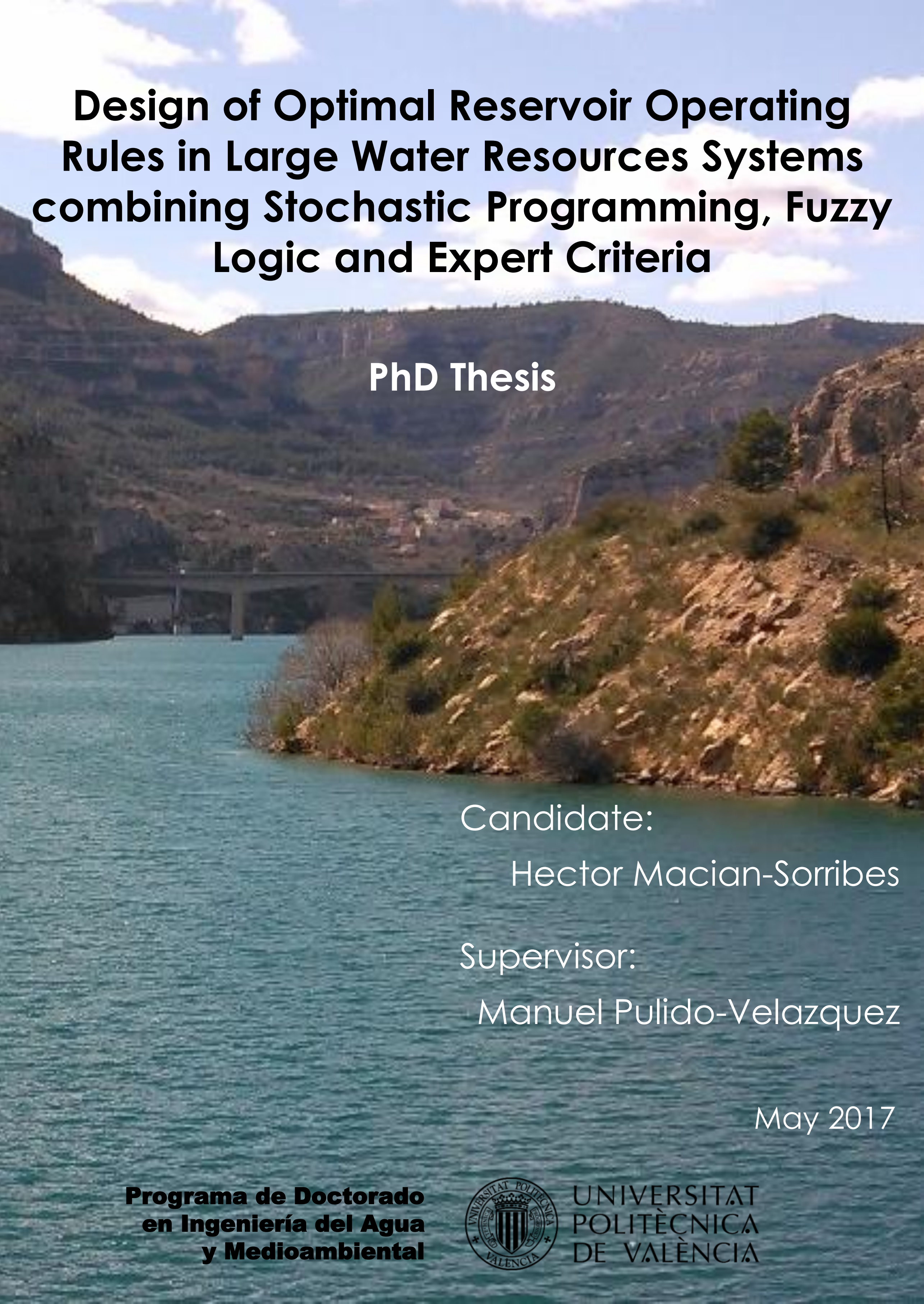

Design of Optimal Reservoir Operating Rules in Large Water Resources Systems combining Stochastic Programming, Fuzzy Logic and Expert Criteria

PhD Thesis

Candidate:

Hector Macian-Sorribes

Supervisor:

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May 2017

Programa de Doctorado en Ingeniería del Agua y Medioambiental

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This PhD Thesis is not an end. It is a beginning.

The parent's duty is to raise their children; the children's duty is to honor their parents. This PhD Thesis is the best but poor way I have found to honor them.

The only source of knowledge is experience

Albert Einstein, scientist

A solution is not merely a set of functions of time, or a set of numbers, but a rule telling the decisionmaker what to do; a policy

Richard R. Bellman, researcher and father of the Dynamic Programming technique

Wine? Thanks to the aqueducts built, we have secured that no roman will be thirsty

Caesar Augustus, roman emperor.

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A researcher cannot successfully confront the requirements of a PhD alone. Nothing of this would have ever been possible without the help received by all the people and funding institutions appearing here. For that, I want to address all of them using different languages, in accordance with the one mostly employed in our day-to-day conversations.

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Many thanks to all of you!

SUMMARY

Given the high degree of construction of hydraulic infrastructure in the developed countries, and with the increasing opposition to constructing new facilities in developing countries, the focus of water resource system analysis has turned into defining adequate operation strategies. Better management is necessary to cope with the challenge of supplying increasing demands and conflicts on water allocation while facing climate change impacts. To do so, a large set of mathematical simulation and optimization tools have been developed. However, the real application of these techniques is still limited. One of the main lines of research to fix this issue regards to the involvement of experts' knowledge in the definition of mathematical algorithms. To define operating rules in a way in which system operators could rely, their expert knowledge should be fully accounted and merged with the results from mathematical algorithms.

This thesis develops a methodological framework and the required tools to improve the operation of large-scale water resource systems. In such systems, decision-making processes are complex and supported, at least partially, by the expert knowledge of decision-makers. This importance of expert judgment in the operation strategies requires mathematical tools able to embed and combine it with optimization algorithms.

The methods and tools developed in this thesis rely on stochastic programming, fuzzy logic and the involvement of system operators during the whole rule-defining process. An extended stochastic programming algorithm, able to be used in large-scale water resource systems including stream-aquifer interactions, has been developed (the CSG-SDDP). The methodological framework proposed uses fuzzy logic to capture the expert knowledge in the definition of optimal operating rules. Once the current decision-making process is fairly reproduced using fuzzy logic and expert knowledge, stochastic programming results are introduced and thus the performance of the rules is improved.

The framework proposed in this thesis has been applied to the Jucar river system (Eastern Spain), in which scarce resources are allocated following complex decision-making processes. We present two applications. In the first

one, the CSG-SDDP algorithm has been used to define economically-optimal conjunctive use strategies for a joint operation of reservoirs and aquifers. In the second one, we implement a collaborative framework to couple historical records with expert knowledge and criteria to define a decision support system (DSS) for the seasonal operation of the reservoirs of the Jucar River system. The co-developed DSS tool explicitly reproduces the decision-making processes and criteria considered by the system operators. Two fuzzy logic systems have been developed and linked with this purpose, as well as with fuzzy regressions to preview future inflows. The DSS developed was validated against historical records. The developed framework offers managers a simple way to define a priori suitable decisions, as well as to explore the consequences of any of them. The resulting representation has been then combined with the CSG-SDDP algorithm in order to improve the rules following the current decision-making process.

Results show that reducing pumping from the Mancha Oriental aquifer would lead to higher systemwide benefits due to increased flows by stream-aquifer interaction. The operating rules developed successfully combined fuzzy logic, expert judgment and stochastic programming, increasing water allocations to the demands by changing the way in which Alarcon, Contreras and Tous are balanced. These rules follow the same decision-making processes currently done in the system, so system operators would feel familiar with them. In addition, they can be contrasted with the current operating rules to determine what operation options can be coherent with the current management and, at the same time, achieve an optimal operation.

RESUMEN

Dado el alto número de infraestructuras construidas en los países desarrollados, y con una oposición creciente a la construcción de nuevas infraestructuras en los países en vías de desarrollo, la atención del análisis de sistemas de recursos hídricos ha pasado a la definición de reglas de operación adecuadas. Una gestión más eficiente del recurso hídrico es necesaria para poder afrontar los impactos del cambio climático y de la creciente demanda de agua. Para lograrlo, un amplio abanico de herramientas y modelos matemáticos de optimización se han desarrollado. Sin embargo, su aplicación práctica en la gestión hídrica sigue siendo limitada. Una de las más importantes líneas de investigación para solucionarlo busca la involucración de los expertos en la definición de dichos modelos matemáticos. Para definir reglas de operación en las cuales los gestores confíen, es necesario tener en cuenta su criterio experto y combinarlo con algoritmos de optimización.

La presente tesis desarrolla una metodología, y las herramientas necesarias para aplicarla, con el fin de mejorar la operación de sistemas complejos de recursos hídricos. En éstos, los procesos de toma de decisiones son complicados y se sustentan, al menos en parte, en el juicio experto de los gestores. Esta importancia del criterio de experto en las reglas de operación requiere herramientas matemáticas capaces de incorporarlo en su estructura y de unirlo con algoritmos de optimización.

Las herramientas y métodos desarrollados se basan en la optimización estocástica, en la lógica difusa y en la involucración de los expertos durante todo el proceso. Un algoritmo estocástico extendido, capaz de ser usado en sistemas complejos con interacciones río-acuífero se ha desarrollado (el CSG-SDDP). La metodología definida usa lógica difusa para capturar el criterio de experto en la definición de reglas óptimas. En primer lugar se reproducen los procesos de toma de decisiones actuales y, tras ello, el algoritmo de optimización estocástica se emplea para mejorar las reglas previamente obtenidas.

La metodología propuesta en esta tesis se ha aplicado al sistema Júcar (Este de España), en el que los recursos hídricos son gestionados de acuerdo a complejos procesos de toma de decisiones. La aplicación se ha realizado de

dos formas. En la primera, el algoritmo CSG-SDDP se ha utilizado para definir una estrategia óptima para el uso conjunto de embalses y acuíferos. En la segunda, la metodología se ha usado para reproducir las reglas de operación actuales en base a criterio de expertos. La herramienta desarrollada reproduce de forma explícita los procesos de toma de decisiones seguidos por los operadores del sistema. Dos sistemas lógicos difusos se han empleado e interconectado con este fin, así como regresiones difusas para predecir aportaciones. El Sistema de Ayuda a la Decisión (SAD) creado se ha validado comparándolo con los datos históricos. La metodología desarrollada ofrece a los gestores una forma sencilla de definir decisiones *a priori* adecuadas, así como explorar las consecuencias de una decisión concreta. La representación matemática resultante se ha combinado entonces con el CSG-SDDP para definir reglas óptimas que respetan los procesos actuales.

Los resultados obtenidos indican que reducir el bombeo del acuífero de la Mancha Oriental conlleva una mejora en los beneficios del sistema debido al incremento de caudal por relación río-acuífero. Las reglas de operación han sido adecuadamente desarrolladas combinando lógica difusa, juicio experto y optimización estocástica, aumentando los suministros a las demandas mediante modificaciones el balance de Alarcón, Contreras y Tous. Estas reglas siguen los procesos de toma de decisiones actuales en el Júcar, por lo que pueden resultar familiares a los gestores. Además, pueden compararse con las reglas de operación actuales para establecer qué decisiones entre las posibles serían coherentes con la gestión actual y, a la vez, óptimas.

RESUM

Donat l'alt nombre d'infraestructures construïdes en els països desenrotllats, i amb una oposició creixent a la construcció de noves infraestructures en els països en vies de desenrotllament, l'atenció de l'anàlisi de sistemes de recursos hídrics ha passat a la definició de regles d'operació adequades. Una gestió més eficient del recurs hídric és necessària per a poder afrontar els impactes del canvi climàtic i de la creixent demanda d'aigua. Per a aconseguir-ho, una amplia selecció de ferramentes i models matemàtics d'optimització s'han desenrotllat. No obstant això, la seua aplicació pràctica en la gestió hídrica continua sent limitada. Una de les més importants línies d'investigació per a solucionar-ho busca la col·laboració activa dels experts en la definició dels models matemàtics. Per a definir regles d'operació en les quals els gestors confien, és necessari tindre en compte el seu criteri expert i combinar-ho amb algoritmes d'optimització.

La present tesi desenrotlla una metodologia, i les ferramentes necessàries per a aplicar-la, amb la finalitat de millorar l'operació de sistemes complexos de recursos hídrics. En estos, els processos de presa de decisions són complicats i se sustenten, almenys en part, en el juí expert dels gestors. Esta importància del criteri d'expert en les regles d'operació requereix ferramentes matemàtiques capaces d'incorporar-lo en la seua estructura i d'unir-lo amb algoritmes d'optimització.

Les ferramentes i mètodes desenrotllats es basen en l'optimització estocàstica, en la lògica difusa i en la col·laboració activa dels experts durant tot el procés. Un algoritme estocàstic avançat, capaç de ser usat en sistemes complexos amb interaccions riu-aqüífer, s'ha desenrotllat (el CSG-SDDP) . La metodologia definida utilitza lògica difusa per a capturar el criteri d'expert en la definició de regles òptimes. En primer lloc es reprodueixen els processos de presa de decisions actuals i, després d'això, l'algoritme d'optimització estocàstica s'empra per a millorar les regles prèviament obtingudes.

La metodologia proposada en esta tesi s'ha aplicat al sistema Xúquer (Est d'Espanya), en el que els recursos hídrics són gestionats d'acord amb complexos processos de presa de decisions. L'aplicació s'ha realitzat de dos

formes. En la primera, l'algoritme CSG-SDDP s'ha utilitzat per a definir una estratègia òptima per a l'ús conjunt d'embassaments i aqüífers. En la segona, la metodologia s'ha usat per a reproduir les regles d'operació actuals basant-se en criteri d'experts. La ferramenta desenvolupada reprodueix de forma explícita els processos de presa de decisions seguits pels operadors del sistema. Dos sistemes lògics difusos s'han empleat i interconnectat amb este fi, al igual què regressions difuses per preveure cabdals. El Sistema d'Ajuda a la Decisió (SAD) creat s'ha validat comparant-lo amb les dades històriques. La metodologia desenvolupada ofereix als gestors una manera senzilla de definir decisions *a priori* adequades, així com per explorar les conseqüències d'una decisió concreta. La representació matemàtica resultant s'ha combinat amb el CSG-SDDP per a definir regles òptimes que respecten els processos actuals.

Els resultats obtinguts indiquen que reduir el bombament de l'aqüífer de la Mancha Oriental comporta una millora en els beneficis del sistema a causa de l'increment de l'aigua per relació riu-aqüífer. Les regles d'operació han sigut adequadament desenrotllades combinant lògica difusa, juí expert i optimització estocàstica, augmentant els subministres a les demandes per mitjà de modificacions del balanç d'Alarcón, Contreras i Tous. Estes regles segueixen els processos de presa de decisions actuals en el Xúquer, per la qual cosa poden resultar familiars als gestors. A més, poden comparar-se amb les regles d'operació actuals per a establir quines decisions entre les possibles serien coherents amb la gestió actual i, al mateix temps, òptimes.

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1. INTRODUCTION

1.1. ROLE OF OPTIMIZATION IN WATER RESOURCES

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

Given the threaten of climate change, as well as the rising population, economic development and living standards causing increasing water demands, the need of improving water resource systems efficiency is expected to keep growing.

A large set of mathematical modeling tools has been developed to achieve an efficient and integrated use of water resources (Labadie, 2004; Lund et al., 2017; Rani and Moreira, 2010; Simonovic, 1992; Singh, 2012; Wurbs, 1993; Yeh, 1985). All of them regard to the system features (physical, hydrological, economic, institutional and so on) to find out how it should be managed (storage levels, releases, demand deliveries, pumping rates, etc.). These models can be divided mainly in simulation and optimization. In the first ones, the system operating rules are described and introduced in the model to find out the performance level associated with them. On the other hand, optimization selects a set of values of the decision variables from the feasible region that maximizes or minimizes an objective function (Rani and Moreira, 2010; Wurbs, 1993). In an optimization procedure, system operating rules may be introduced as part of the system model description (as constraints) or in the objective function (as goals).

Simulation models can assume detailed system representations in both its features and operation strategies, but cannot derive improved operating rules in a proper way (Labadie, 2004). On the contrary, optimization models are powerful tools to obtain more efficient management decisions, but their results should be post-processed to transform them into suitable operating rules (Oliveira and Loucks, 1997). Optimization models have intrinsic limitations that hinder their use in decision-making (Labadie, 2004; Rogers and Fiering, 1986). It should be taken into account that the decisions obtained by them are only optimal for the mathematical model of the system they assume. Reality is more complex than a mathematical model, so results need to be adapted to the decision-making processes carried out in real-life.

All these facts have hurdled the real-life applicability of optimization procedures during the last decades, creating a gap between theory and practice (Labadie, 2004; Oliveira and Loucks, 1997; Rani and Moreira, 2010; Simonovic, 1992; Wurbs, 1993; Yeh, 1985). In the present day, this gap has been significantly narrowed thanks to advances in the computation power, the increasing usage of decision support systems (DSS) including optimization models (Labadie, 2004), and the use of evolutionary optimization algorithms able to consider multiple objectives and trade-offs between them (Maier et al., 2014; Rani and Moreira, 2010). Hydropower systems, which are mostly operated following an economic objective easy to be quantified, are often managed employing real-time optimization models (Lund et al., 2017). In addition, optimization algorithms are also used, as simulation ones, in the long-term planning and the development of adaptation measures to face climate change impacts (e.g. Girard et al., 2015).

In spite of this progress and the increasing interest of decision-makers in improved operating rules, there is still a lack of uptake of optimization models by the operators of complex water resource systems (characterized by multiple and conflicting performance criteria and different points of view), who keep relying mostly on simulation techniques (Maier et al., 2014; Rani and Moreira, 2010). This is particularly true in the case of the seasonal operation (up to one year in advance), given that agricultural decision-making includes decisions (such as the cropping pattern) that should be maintained during certain period (e.g. Marques et al., 2005). The main reasons behind this gap is the lack of involvement of system operators in the models' development, the choice of inappropriate methodologies to estimate operating rules based on optimization results (Labadie, 2004), and the fact that good system operation is a subjective concept, depending upon the stakeholders' views (Maier et al., 2014; Oliveira and Loucks, 1997).

In order to improve the level of implementation of optimization models in the decision-making processes carried out in complex water resource systems, several alternatives have been pointed out in the literature, among them:

1) Increasing the involvement of decision-makers in the development of optimization algorithms (Labadie, 2004; Maier et al., 2014).
2) Improving the linkage between simulation and optimization models (Labadie, 2004; Rani and Moreira, 2010).
3) Adequately framing optimization methods in the decision-making processes, in which they should be perceived as part of wider management practices (Maier et al., 2014; Oliveira and Loucks, 1997).

With regard to the linkage between simulation and optimization models, computational intelligence and heuristic methods are recognized as the most promising alternatives due to its ability to be linked with simulation models (Labadie, 2004; Maier et al., 2014; Rani and Moreira, 2010). Considering the framing in decision-making, it is crucial to adapt them to the processes carried out in reality, since sometimes rules are used in the context of a broader scope, including negotiation and agreement reaching (Maier et al., 2014; Oliveira and Loucks, 1997). Under these circumstances, operating rules should provide guidance to the system operators, exploring promising management alternatives for further examination rather than finding an optimal course of action (Maier et al., 2014). If optimization algorithms are desired to be applied in simulation models reflecting the decision-making processes, it is required to transform their results into operating rules expressed in a way in which system operators rely. To achieve this, close cooperation between researchers and decision-makers is necessary, involving the latter from the beginning in order to receive a continuous feedback and adapt the research outcomes to their needs and practices.

1.2. GOALS AND OBJECTIVES

The main goal pursued is the development of methods and tools for improving the operation of large-scale water resource systems (comprised of both several reservoirs and aquifers and in which surface and ground waters interact). This improvement is measured by the increase in monetary revenues (hydroeconomic approach) and by the rise in deliveries to the system demands (in line with the metrics established by the case study River Basin Authority).

The proposed research takes into account the interaction between surface and groundwater bodies; as well as the different decision-making processes, modeling requirements and time horizons possessed by surface and groundwater resources. The current decision-making practices and operating rules are reproduced in this thesis using heuristic procedures, given their potential to be linked with mathematical simulation models. Decision-makers are actively involved in the assessment and reproduction of the current operation processes and the building of the tools defined in this thesis. The suitability of the developments is tested in the Jucar river system (Eastern Spain).

In order to implement the main goal and determine its degree of achievement, the following research objectives with regard to the methods and the case study applications have been defined. The ones related to the methods can be stated as:

- Development of an optimization algorithm able to define optimal conjunctive operation decisions of large-scale water resource systems, considering both inflow uncertainty and interactions between surface and groundwater bodies.
- Build-up of a methodology capable of reproducing and improving the seasonal operation of a large-scale water resource system. It should be able to merge expert judgment, observed historical decisions and optimization results into a Decision Support System (DSS).
- Building of Decision Support System shells able to implement the previously defined algorithm, as well as the resulting improved operating rules.

The objectives related to the case study, using the methods previously developed, are the following:

- Definition of an improved conjunctive use operation of the Jucar river system, taking into account how reservoirs and groundwater bodies interact.
- Reproduction of the current decision-making processes of the Jucar river system seasonal operation. This reproduction will be built in close

collaboration with the system operators, in order to assure its adequacy to the current practices and to acquire their expert judgment. It will be validated against historical records to ensure its suitability.

- Application of the optimization algorithm previously developed to define optimal seasonal operating rules respecting the current decision-making processes.

1.3. METHODS AND MAIN ASSUMPTIONS

In order to address the goals and objectives pointed out previously, the methods used must have specific features. In particular, the optimization algorithm should be applicable to large-scale systems (like the Jucar system) and consider inflow uncertainty in decision-making (given the long droughts – high inflow correlation – faced by the Jucar river system). This algorithm will be used with the focus on the system operation. On the other hand, the method employed to reproduce the system operation should be able to combine expert knowledge and optimization results, as well as to be easy understood by decision-makers without strong foundations on it. The state-of-the-art of both the optimization algorithms and the procedures to mathematically reproduce operating rules is presented in Chapter 2, including the advantages and limitations of the main approaches followed in the literature so far.

The analysis period will cover mainly the first decade of the 21st century. The system features considered in the analysis (inflows, demands, environmental requirements and so on) will correspond to this period. The time span choice is conditioned by the need of validating the current operating rules and decision-making processes against historical records. Applying the analyses carried out in this thesis to future climatic conditions would require to continuously update the models at the light of the forecasted future climate.

Considering the issues pointed out previously, this PhD thesis relies on two mathematical methods: stochastic programming and fuzzy logic. The first one will be used to obtain time series of optimal decisions, while the second will be employed to support seasonal operation representing the current practices of the system. Fuzzy logic will also be used to transform optimization results into operating rules, taking into account expert judgment.

Explicit stochastic programming is a family of optimization techniques in which a probabilistic description of inflows is included within the algorithm structure (Labadie, 2004). It has been chosen in this thesis because it does not work with perfect foreknowledge of future inflows, a phenomenon that would make the obtained decisions optimal just for the hydrologic time series analyzed (Labadie, 2004). This issue becomes relevant in river systems like the Jucar, subject to drought operating conditions, as optimal decisions from deterministic programming algorithms would not provide an adequate hedging strategy (Rani and Moreira, 2010).

Among the stochastic optimization algorithms available, SDDP (Pereira and Pinto, 1991, 1985) is one of the few alternatives able to optimize large-scale water resource systems due to its reduction of the computational burden suffered by SDP when the number of state variables increase (Goor, 2010; Rani and Moreira, 2010). Furthermore, SDDP has been long used in large-scale system applications in which hydropower, agriculture and urban uses coexist (Rani and Moreira, 2010).

SDDP has been combined in this thesis with the stream-aquifer interaction model EMM (Embedded Multireservoir Model, Pulido-Velazquez et al., 2005). EMM's formulation is based on the structure of the analytical solution of the stream-aquifer interaction problem obtained from the groundwater flow equation applied into linear systems (confined aquifers or unconfined aquifers with negligible head variations compared with its thickness), as well as its analogy with the state equation of the groundwater linear reservoir model (Sahuquillo, 1983). It represents stream-aquifer interaction as the summation of the drainage of one or more reservoirs with discharges linearly proportional to the volume store above the outlet. Although the EMM is unable to obtain spatially-distributed heads, it has been shown to provide accurate representations of stream-aquifer interactions, even in complex cases such as karstic aquifers (Estrela and Sahuquillo, 1997). Further information on analytical and numerical derivations of the EMM can be found in Pulido-Velazquez et al. (2008, 2006a, 2005).

The resulting algorithm, the CSG-SDDP, is able to obtain optimal decisions under inflow uncertainty considering the influential stream-aquifer interactions. These decisions consist of reservoir releases, demand deliveries and pumping rates from aquifers. In spite of its ability to define optimal decisions making a joint operation of reservoirs and aquifers, the inclusion of groundwater bodies enlarges the size of the optimization problem and thus the computational requirements. However, they do not grow enough to suppose a challenge in terms of the computational power required. Moreover, the characterization of stream-aquifer interactions requires detailed information on groundwater behavior. The algorithm is also subject to the features of any hydroeconomic procedure (need of enough information to build the economic characterization of the system), the SDDP algorithm (social planner approach, single objective optimization), the EMM (not modeling groundwater heads and internal groundwater flows), and the social planner perspective (perfect cooperation is assumed).

Assuming that heuristic procedures offer the most efficient way to reproduce complex decision-making processes and operating rules, as well as being easily combined with simulation algorithms (Labadie, 2004; Rani and Moreira, 2010), decision moves to choosing the right heuristic method. Fuzzy logic (Mamdani, 1974; Zadeh, 1965), is one of the most popular derivations of the fuzzy set theory. It is an alternative to the classic or Boolean logic in which fuzzy sets and fuzzy numbers are used to quantify the inputs and outputs of each logical or IF-THEN rule. A fuzzy logic system or fuzzy rule-based system is a collection of fuzzy logic rules mapping inputs to outputs, as done by other heuristic procedures like Artificial Neural Networks or Bayesian networks. In terms of its efficiency in reproducing complex decision-making processes and rules, fuzzy logic offers a similar performance level than other heuristic methods.

Fuzzy logic has been chosen in this PhD thesis mainly due to its ability to accommodate expert knowledge in its construction, to combine it with data-based information sources and to link language with mathematics. Thanks to this, fuzzy logic can be intuitively perceived and easy to be understood and managed by people not familiar with its foundations (Pedrycz et al., 2011; Sen, 2010). Furthermore, fuzzy logic is better suited to situations in which data availability is scarce, in contrast to Artificial Neural Networks or

Bayesian networks, which require more data records to be fully operative. On the contrary, fuzzy logic can easily replace this lack of data by expert knowledge.

1.4. STRUCTURE OF THE DOCUMENT

This document has been divided into 8 chapters, going from an introduction to the conclusions through the state-of-the-art review, the presentation of the methods and tools developed, the two different applications to the Jucar river system and the results. Finally, conclusions and further research lines are identified, followed by the list of dissemination activities and the references.

The introductory chapter (Chapter 1) presents the context, exposition of goals, objective, methods and assumptions.

The state-of-the-art review (Chapter 2) has been divided into two parts. The first one is devoted to defining optimal operating rules, including the frameworks and mathematical tools employed so far. The second one regards to the use of the fuzzy set theory in water resources, focusing on fuzzy logic, fuzzy regression and the ways to represent expert knowledge.

The materials and methods part is covered in two chapters. Chapter 3 presents the extension of the SDDP algorithm to take into account stream-aquifer interactions, able to define optimal conjunctive use strategies. It also includes the description of the ESPAT tool, the general-purpose DSS shell created to perform CSG-SDDP runs. Chapter 4 describes the framework developed in this thesis con combine fuzzy logic, stochastic programming and expert knowledge to define optimal operating rules adapting to the system operators' requirements and processes.

The application of the materials and methods to the case study, the Jucar river system, is presented in the next three chapters. Chapter 5 introduces the system and its operation. Chapter 6 focuses on the definition of an optimal conjunctive use strategy for the system. Chapter 7 presents a collaborative framework to couple historical records with expert knowledge and criteria to define a decision support system (DSS) that helps on the seasonal operation of the Jucar river system. The framework relies on the co-development of a DSS tool, based on fuzzy logic, which explicitly reproduces the decision-making processes and criteria followed by the system operators. Optimization results are used to improve the system operating rules.

Chapter 8 consists of a summary of the thesis and the conclusions drawn from it with regard to the application of the methods to the Jucar river system, and outlines several investigation lines that could be further explored based on the results of this thesis.

2. STATE-OF-THE-ART

The following state of the art is divided in two main parts. The first one reviews the methods employed in the design of operating rules based on optimization models. In the second one, the use of fuzzy logic in water resources is described, as well as fuzzy regression and how expert knowledge can be modeled. Finally, some remarks about optimization procedures applied to large-scale systems with reservoirs and aquifers are given.

2.1. DEVELOPMENT OF RESERVOIR OPERATING RULES

Mutireservoir systems management has been extensively studied in the literature, usually employing computer simulation or optimization models, or combinations of both (Labadie, 2004; Oliveira and Loucks, 1997; Rani and Moreira, 2010; Simonovic, 1992; Singh, 2012; Wurbs, 1993; Yeh, 1985). The mathematical representation of optimal system operations has been addressed by three different approaches in the literature: using an optimization algorithm for real-time operation based on the system state and some forecasting tools; developing *a priori* reservoir operating rules; and building a representation of the implicit reservoir operating rules. In the last two, operating rules need to be explicitly expressed. These rules can take many forms, from simple to complex mathematical formulations, and should indicate the actions to be taken by the system operators depending on the system conditions expressed through variables like storage state, time of the year and forecasted hydrology (Loucks and van Beek, 2005; Lund et al., 2017; Oliveira and Loucks, 1997).

For deriving optimal operating rules, it is necessary to decide how they are going to be obtained and the mathematical representation to be used. Both decisions are linked, since the formulation of the rules can condition the way they are estimated, and some of the methods developed to design operating rules are restricted to one or several rule forms.

2.1.1. Deriving operating rules from optimization models

Although systems' optimization models have been long used for water resources planning and management, the conversion of their results into operating rules is not easy and direct (Lund, 1996). The alternatives existing to do so consist of the direct use of optimization results, the definition of operating rules with *a priori* rule forms, or the inference of rules from optimization results. In order to choose the right alternative, one should take into account the case study features and the purpose of the operating rules.

Direct optimization of the system's operation

Optimization models have been largely employed for analyzing potential improvements in the operation of water resource systems (e.g. Labadie, 2004; Rani and Moreira, 2010; Simonovic, 1992; Singh, 2012; Wurbs, 1993; Yakowitz, 1982; Yeh, 1985). Regarding the purpose of the algorithm and its time horizon, its use can be divided into two categories: long-term optimization and real-time optimal control with forecasting.

Long-term optimization

This option employs an optimization algorithm applied to long-term periods (monthly time steps with planning horizons of more than a decade) in order to extract and analyze the *ideal* operation of the system and its associated performance. The goal of the analysis is not to derive an entire set of operating rules, but to suggest certain aspects of the system management that could be changed to improve its efficiency. This category can accommodate a wide range of algorithms, including deterministic (implicit stochastic) optimization, stochastic (explicit stochastic) optimization and heuristic optimization (Fig. 2.1).

The **implicit stochastic optimization (ISO)** approach consists in using deterministic programming procedures to optimize a large set of inflow time series (one long inflow sequence or several shorter ones) in order to capture most of the stochastic aspects included in the problem (Labadie, 2004; Mousavi et al., 2005; Rani and Moreira, 2010). The general optimization equation is:

$$F = \max_{r_t} \sum_{t} B_t(s_t, r_t, q_t) \tag{2.1}$$

Where F total benefit, B_t benefit obtained in time stage t; r_t optimal decision made during time stage t; s_t initial storage at time stage t; and q_t inflow during time stage t. This equation is subject to the mass balance between s_t and s_{t+1}, and to the variables' bounds constraints. Implicit stochastic programming is mainly divided into linear programming, non-linear programming and dynamic programming (Labadie, 2004; Rani and Moreira, 2010; Yeh, 1985).

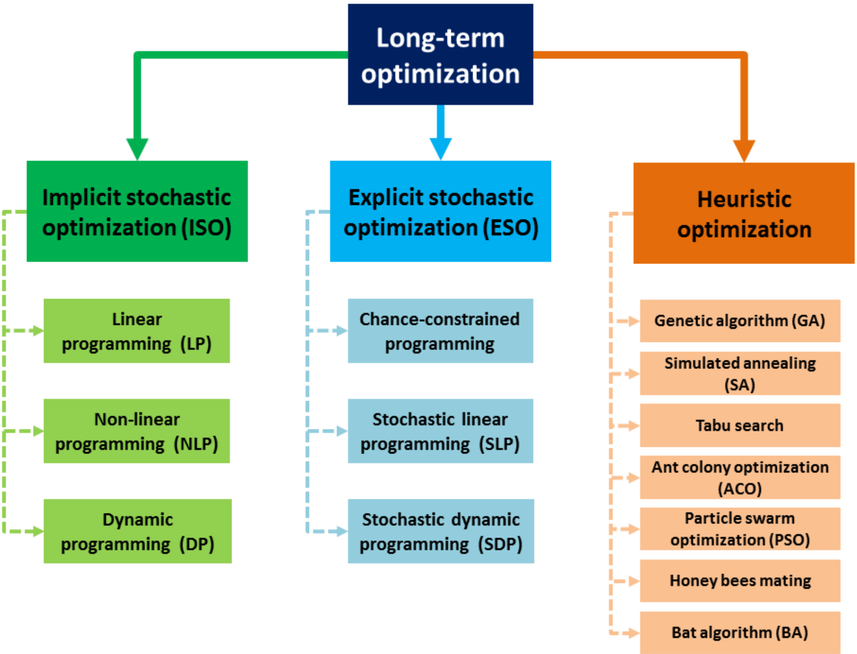


Fig. 2.1: Long-term optimization algorithm classification

The primary advantage of this approach is the ability of deterministic programming algorithms to be applied in large water resource systems, thus being able to solve complex problems with less simplification needs than stochastic programming. However, they are subject to the perfect foresight phenomenon: since the allocation decisions are optimized for the whole inflow time series, the problem knows future inflows in advance, having an unrealistic advantage. This phenomenon implies that the optimal decisions obtained are unique to the assumed hydrologic time series (Labadie, 2004). The optimization problem can be solved through linear programming (LP), non-linear programming (NLP) and dynamic programming (DP).

In linear programming (LP) algorithms, both the objective function and the constraints are expressed using linear equations (Yakowitz, 1982; Yeh, 1985). Its advantages are its efficiency, its global optimum convergence guarantee, the non-necessity of a starting point for the calculations and a developed duality theory (Labadie, 2004). Its main disadvantage is the necessity of a linear problem, which sometimes requires the assumption of simplifications or previous analyses to turn all the mathematical relationships into linear (Rani and Moreira, 2010).

Non-linear programming (NLP) algorithms are required when the problem cannot be transformed into a linear one. In comparison with LP, non-linear programming algorithms are slower, iterative, resource-consuming and in need of a starting point (Simonovic, 1992). However, they are able to obtain optimal solutions when linear programming problems cannot be applied (Simonovic, 1992). When applying a non-linear programming method, one should be aware of the starting point used, since the solver may fail in finding an optimal solution depending on it. In order to tackle this issue, Cai et al. (2001) developed a piece-by-piece approach in which the problem was decomposed into several subproblems that were sequentially solved using as starting point the solution of the previous one. This scheme succeeded in avoiding solver's failure, reducing the problem's complexity and decreasing the time required. Examples of NLP can be found in Cai et al, (2001); Satti et al. (2015); Theodossiou (2004); and Vieira et al. (2011).

Dynamic programming (DP, Bellman 1957) is one of the most popular optimization techniques for sequential decision-making (Simonovic, 1992; Yakowitz, 1982; Yeh, 1985). Dynamic programming approaches multistage optimization problems by decomposing them into series of single-stage problems that are sequentially solved (Labadie, 2004; Rani and Moreira, 2010; Simonovic, 1992). This procedure reduces the computational effort required to solve the multistage problem and tackles its non-linearities in an efficient way (Labadie, 2004; Nandalal and Bogardi, 2007).

In its original form, also named as discrete dynamic programming (DDP), the state and decision variables (usually initial and final storages) are discretized for each time stage. Then, for all combinations of discrete storages, the benefit function $F_t(s_t)$ is recursively optimized moving (usually) backwards between the end of the planning horizon ($t=T$) and the present ($t=1$). To do so, the Bellman equation must be solved for each and every time stage t (Labadie, 2004; Nandalal and Bogardi, 2007; Rani and Moreira, 2010):

$$F_t(s_t) = \max_{r_t}[B_t(s_t, r_t) + F_{t+1}(s_{t+1})] \qquad \textbf{2.2}$$

Were s_t discrete initial storage at time stage t; r_t decision (release or final storage) made, B_t immediate benefits obtained from the system operation at time stage t, which are the results of the previous solver executions; F_{t+1} benefits-to-go between time stage $t+1$ and the end of the planning horizon; and s_{t+1} discrete initial storage at time stage $t+1$.

The main drawback of DDP is the discretization of variables, since only combinations of the discrete states previously defined are considered when finding an optimal solution. Consequently, accurate solutions require the use of finer discretizations, which increase the number of solver executions and thus the computational costs. This phenomenon is known as *the curse of dimensionality* (Labadie, 2004). In order to alleviate it, several modifications of the original DP algorithm have been developed (Labadie, 2004; Rani and Moreira, 2010): incremental DP (IDP), discrete differential DP (DDDP), DP with successive approximations (DPSA), differential DP (DDP), constrained differential DP (CDDP) and so on. Examples of DP can be found in Grüne and Semmler (2004); Hall and Buras (1961); Johnson et al. (1993); Liu et al. (2011); Nandalal and Bogardi (2007); and Turner and Galelli (2015).

The main difference between the ISO and the **explicit stochastic optimization (ESO)** approach is that the latter uses stochastic programming algorithms. These algorithms embed probabilistic descriptions of inflows, thus the optimization is performed without the assumption of perfect inflow foreknowledge (Labadie, 2004; Rani and Moreira, 2010):

$$F = \max_{r_t} E\left[\sum_t B_t(s_t, r_t, q_t)\right]_q \qquad \textbf{2.3}$$

Where F total benefit obtained; r_t optimal decision made during time stage t; E expectation operator; B_t benefits obtained through the system operation in time stage t; s_t initial storage at time stage t; and q_t inflow during time stage t. This equation is subject to the mass balance between s_t and s_{t+1}, and to the variables' bounds constraints.

The main advantage of ESO is the absence of the perfect foresight phenomenon, thus achieving efficiency levels that could be attainable in real life. Furthermore, these methods directly obtain optimal rules without the (theoretical) need of *ex post* analyses (Labadie, 2004). On the other hand, they are more computationally challenging than ISO, since they embed the inflows' probabilistic description within its formulation (Labadie, 2004). Moreover, the form in which the operating rules are obtained by default is method-dependent and may not match the desired one. Explicit stochastic optimization algorithms can be mainly divided in chance-constrained programming, stochastic linear programming and stochastic dynamic programming.

In the chance-constrained programming algorithm, inflows are treated as random variables with a probability distribution. A risk level is established and the operation decisions are bond to it (Eisel, 1972; Revelle et al., 1969). The lower the risk level is, the tough the restrictions are and thus the more conservative is the operation of the system (Labadie, 2004). The main drawback associated with chance-constrained programming is that the operating rules obtained are more conservative than the risk level assumed by the optimization algorithm, requiring further Monte Carlo analyses to determine their true risk level and iterative processes to adjust it to the desired limits (Labadie, 2004). Furthermore, the temporal correlation of inflows is not taken into account. Examples of chance-constrained applications can be found in Eisel (1972); Houck (1979); Revelle et al. (1969); Sahinidis (2004); Xu et al. (2017); and Zeng et al. (2013).

Stochastic linear programming (SLP) models operate under the assumption that current decisions can be made with certain information, but future ones are subject to growing uncertainties (Labadie, 2004). Consequently, the problem is built as a two-stage one, in which the goal is to maximize the benefits obtained with the current (first stage) decisions plus the expected benefits of the future decisions (second stage), which depend on the current ones and future random inflows (Marques et al., 2005). The algorithm is executed each time stage to obtain the best decision and the information is updated time stage after time stage. Its primary advantage is that it efficiently divides the decision-making process according to the uncertainty level: one stage without uncertainty and other one with uncertainty. Its main disadvantage is that inflow scenarios are required for the second stage and, unless a reduced number of them are chosen, the problem becomes computationally challenging (Labadie, 2004).

Stochastic dynamic programming (SDP, Stedinger et al. 1984) combines the DP methodology with an explicit consideration of inflow uncertainty (Rani and Moreira, 2010). Its general equation combines the DP one with the general explicit stochastic programming formulation:

$$F_t(s_t) = \max_{r_t} E[B_t(s_t, r_t, q_t) + F_{t+1}(s_{t+1}, q_t)]_q \qquad \textbf{2.4}$$

Were F_t total benefits between time stage t and the end of the planning horizon; s_t initial storage at time stage t; r_t decision (release or final storage) made; E expectation operator; B_t immediate benefits obtained from the system operation at time stage t; q_t inflows during time stage t; F_{t+1} benefits-to-go between time stage $t+1$ and the end of the planning horizon; and s_{t+1} initial storage at time stage $t+1$.

In its standard formulation, both the storage and the inflow variables are discretized and a probabilistic description in the form of a Markov Chain is used to estimate the probabilities associated with any possible discrete future inflow given the current discrete value (Nandalal and Bogardi, 2007). The main result of the algorithm is the operating rule in the form of a table, in which the optimal decision is provided given any possible discrete storage and inflow combination (Loucks and van Beek, 2005). In this form, SDP possesses the same advantages as deterministic DP but without being subject to the perfect foresight phenomenon. However, it suffers a stronger curse of dimensionality than deterministic DP due to the use of discrete storages and inflows (Labadie, 2004; Rani and Moreira, 2010). Several derivatives of SDP have been developed in order to provide alternative ways to solve stochastic programming problems. The most popular among them are:

- Stochastic dual dynamic programming (SDDP, Pereira and Pinto 1985) uses dual variables to build efficient representations of the benefit-to-go functions, in order to tackle the curse of dimensionality. This approach is explained in more detail in Chapter 3.
- Sampling SDP (SSDP Kelman et al. 1990), in which the discrete inflow values are substituted by a scenario-based approach that partially alleviates the curse of dimensionality.

- Bayesian SDP (BSDP, Karamouz and Vasiliadis 1992), embedding a Bayesian network in a SDP algorithm in order to continuously update the Markov Chain as the hydrological information increases.
- Demand-driven SDP (DDSP, Vasiliadis and Karamouz 1994) that aims at incorporating demand uncertainties in the analysis.
- Fuzzy SDP (FSDP): two derivatives use this name:
    - A SDP variant in which the objectives were expressed using fuzzy sets (Tilmant et al., 2002a).
    - A SDP formulation in which fuzzy transition probabilities, fuzzy reservoir states and/or other fuzzy variables were employed (Mousavi et al., 2004b; Mujumdar and Kumari, 2015).
- Reinforcement learning (Lee and Labadie, 2007), whose aim is to tackle the curse of dimensionality by letting the algorithm learn in a continuous way.

Examples of applications of SDP and their derivatives can be found in Nandalal and Bogardi (2007); Pereira-Cardenal et al. (2015); Pereira and Pinto (1991, 1985); Stedinger et al. (1984); Tejada-Guibert et al. (1993); Turner and Galelli (2015); and Zhao et al. (2014).

Heuristic optimization, also known as computational intelligence, evolutionary algorithms or metaheuristics, differs from the previous approaches in the way it addresses the optimization problem. Rather than based on algorithmic procedures following well-founded mathematical theories, heuristic optimization relies on making analogies between the optimization problem and natural processes based on the survival or success of the best (Labadie, 2004). These procedures apply an intelligent search in order to optimize the problem. They do not guarantee the achievement of an optimal solution (even local), but they are able to obtain optimal decisions to problems in which traditional algorithms would fail to converge or would only be able to obtain local optima (Labadie, 2004).

Their main advantage is their efficiency in handling non-linearities and discontinuous variables, their suitability to solve multi-objective procedures and their possibility to be easily linked with simulation models (Labadie, 2004; Maier et al., 2014; Rani and Moreira, 2010). A lot of algorithms have been developed, each of one having their own advantages and disadvantages with respect to the rest. Some of the most common heuristic procedures are:

- Genetic algorithms (GA): based on natural genetics and evolutionary processes. Examples of application can be found in Bozorg-Haddad et al. (2017); Oliveira and Loucks (1997); Reed et al. (2013); and Salazar et al. (2016).
- Simulated annealing (SA): in which the algorithm mimics the annealing process used in glass making or metallurgy (e.g. Teegavarapu and Simonovic, 2002).
- Tabu search (TS): similar to SA processes (Glover and Taillard, 1993) but lightly applied to water resources management.
- Ant colony optimization (ACO): based on how ants find the closest way to food sources (e.g. Safavi and Enteshari, 2016).
- Particle swarm optimization (PSO): similar to GA algorithms.
- Honey bees mating optimization: which reproduces the process with which honey bees meet (e.g. Haddad et al., 2006).
- Bat algorithm (BA): in which the procedure reproduces the echolocation or sonar system employed by the bats when flying (e.g. Bozorg-Haddad et al., 2014).

Real-time optimal control with forecasting

The direct use of an optimization algorithm in real-life operation is only possible at short time horizons (hourly or daily time steps and time spans of weeks or months) and in water resource systems in which the objective is unique and clearly defined, such as maximizing hydropower production or minimizing pumping costs (e.g. Bauer-Gottwein et al., 2015; Caseri et al., 2016; Castelletti et al., 2014; Ficchì et al., 2015; Teegavarapu and Simonovic, 2000).

Most of the real-life applications of optimization algorithms refer to real-time optimal control with forecasting. This method, also known as Model Predictive Control (MPC) with forecasting, is based on the receding horizon principle: the problem is optimized over a finite time horizon, for which a forecast is available, but only the decision obtained for the first time step is implemented. For the next time stage, the problem is re-formulated updating the forecast and solved again, repeating the process from time step to time step (Castelletti et al., 2008; Galelli et al., 2014; Lin and Rutten, 2016). This algorithm construction makes it especially suited to the short-term operation of water resource systems.

For example, consider that, at time stage *t*, a forecast is available for the next *n* stages. An optimal control model would solve the optimization problem for the time horizon [*t, t+n*] using this forecast. However, only the decision obtained for the first time stage (r_1) would be implemented. At time stage *t+1*, the problem would be re-built and solved using an updated forecast for the [*t+1, t+n+1*] period. The process would be repeated each time stage, continuously updating the forecast information.

The main advantages of real-time optimal control are its higher flexibility compared with conventional methods, being also more realistic, and its ability to be included in early warning systems (Jain and Singh, 2003). The flexibility is achieved by continuously updating the control model and the forecast information available.

Regarding the optimization techniques, the same algorithms as presented for the long-term optimization can be used in MPC. The choice depends on the optimization goals, the system features and the available information. Considering the inflow forecasting methods, the main options used so far consist of hydrological and/or hydraulic models forced with meteorological forecasts (Bianucci et al., 2015; Caseri et al., 2016; Côté and Leconte, 2015; Faber and Stedinger, 2001; Ficchì et al., 2015; Pianosi and Ravazzani, 2010; Raso et al., 2014); stochastic autoregressive models predicting inflows based on current streamflows and/or rainfall (e.g. Mizyed et al., 1992; Pianosi and Ravazzani, 2010; Pianosi and Soncini-Sessa, 2009); and decision trees in which future inflows were predicted based on past and present meteorological and hydrological information (e.g. Chazarra et al., 2016; Côté and Leconte, 2015; Galelli et al., 2014; Raso et al., 2014, 2013).

MPC has been mainly applied to urban reservoirs (e.g. Galelli et al., 2014), irrigation and drainage control (e.g. Mizyed et al., 1992; Overloop et al., 2008), hydropower (e.g. Bianucci et al., 2015; Côté and Leconte, 2015; Sordo-Ward et al., 2012; Teegavarapu and Simonovic, 2000), and flood protection (e.g. Caseri et al., 2016; Ficchì et al., 2015; Raso et al., 2014). Comprehensive reviews can be found in Castelletti et al. (2008); and Lin and Rutten (2016).

Using *a priori* operating rule forms

In this approach, the rule form in which the system operation is conceptualized is chosen before running any algorithm, being explicitly included in its formulation. This framework can accommodate optimization algorithms and combined simulation-optimization approaches.

If employing an optimization algorithm, the equations of the chosen rule form are embedded into its formulation. The algorithm is executed to obtain the rule parameter set that maximizes the system's efficiency. Objective functions used in the literature consisted mainly in minimizing the required reservoir capacity (Houck, 1979; Loucks, 1970; Revelle et al., 1969); optimizing a combination of performance indicators (Gundelach and ReVelle, 1975; ReVelle and Gundelach, 1975; Revelle and Kirby, 1970); and maximizing the benefits obtained from operation (Eisel, 1972; Houck et al., 1980; Wan et al., 2016). This process guarantees the achievement of an optimal rule with the given rule form. However, the incorporation of the rule form equations increases the complexity of the optimization problem, thus requiring simplifications that may cause the optimal rules to be ill-defined.

Combined simulation-optimization approaches take advantage of the complementary features possessed by optimization and simulation models. These processes have grown in the last years thanks to the rise of heuristic optimization, which can effectively combine simulation and optimization procedures while handling complex performance criteria (e.g. Ashbolt et al., 2016; Lerma et al., 2015, 2013; Yang and Ng, 2016). The main rule forms assumed by these procedures have been regression equations (e.g. Ahmadi et al., 2014; Bolouri-Yazdeli et al., 2014; Celeste et al., 2009; Fallah-Mehdipour et al., 2012); operating rule curves (e.g. Celeste and Billib, 2009; Lerma et al., 2013; Wan et al., 2016); radial basis functions (e.g. Giuliani et al., 2015); and fuzzy rule-based systems (e.g. Yang and Ng, 2016).

Inferring rules from optimization results

In this approach, an optimization algorithm is executed and its results analyzed in order to define the rule that best fits them. Any optimization procedure can be chosen, based on either deterministic or stochastic programming (Karamouz and Houck, 1987; Labadie, 2004; Rani and Moreira, 2010). The framework of this approach consists in running an optimization model using the historical and/or alternative inflow time series, analyzing its results and deriving operating rules, which are tested using simulation models to refine and validate them and, if required, the optimization model too.

The rule forms mainly employed in the literature are shown in Table 2.1. They have grown in the last years due to the increase in computer power and the emergence of heuristic and knowledge-based procedures such as artificial neural networks or fuzzy rule-based systems.

Table 2.1: Main approaches for inferring rules from optimization results

Rule form family	Examples
Regression equations	Bhaskar and Whitlatch (1980); Huang et al. (2016); Karamouz et al. (1992); Karamouz and Houck (1987, 1982); Loucks (1970); Lund (1996); Lund and Ferreira (1996); Lund and Guzman (1999); Young (1967)
Interpolation equations	Celeste et al. (2009); Davidsen et al. (2014); Tejada-Guibert et al. (1993)
Data mining	Bessler et al. (2003); Hejazi et al. (2008); Hejazi and Cai (2009, 2011); Yang et al. (2016)
Artificial Neural Networks	Chandramouli and Raman (2001); Liu et al. (2006)
Fuzzy Rule-based Systems	Dubrovin et al. (2002); Panigrahi and Mujumdar (2000); Russell and Campbell (1996)
Reinforcement learning	Castelletti et al. (2013, 2010); Lee and Labadie (2007); Madani and Hooshyar (2014)

2.1.2. Mathematical formulations of operating rules

Operating rules obtained from optimization models should link current and predicted state variables (storages, groundwater levels, current and/or forecasted inflows, demands, etc.) with operational decisions (releases, target storages, deliveries and so on). Several mathematical formulations have been developed to address these relationships, growing during the last years due to the development of computational intelligence and heuristic methods. According to their features, they can be mainly divided into four families of methods: empirically-based methods, rules-of-thumb, heuristic procedures and knowledge-based approaches.

Empirically-based operating rules

This family of methods refers to the empirical development of operating rules from the results of optimization algorithms using mathematical equations.

Regression

Regression was the first wide-used mathematical representation of operating rules based on optimization results (Bhaskar and Whitlatch, 1980; Karamouz and Houck, 1982; Loucks, 1970; Revelle et al., 1969; Young, 1967). Its main advantages are the fact that it is easy to apply, conceptually simple and with a wide range of applicability. It is also scalable and easy to be embedded in different optimization and simulation algorithm configurations. Its main drawback is that it may lead to poor correlation coefficients invalidating the obtained rules (Labadie, 2004). Moreover, regression results depend on the pre-fixed regression equation form used, being difficult to tell in advance which could be the best one.

The standard regression procedure consists in assuming an equation form and fitting its coefficients to reproduce as close as possible the optimization results. Optimization procedures are required to determine which coefficients maximize the quality of the regression (evaluated through indices such as the correlation coefficient, the R-squared, the Nash-Sutcliffe coefficient, etc.). The main regression procedures used in water resources management are linear regression, nonlinear regression, piecewise linear regression, fuzzy regression and support vector regression (Table 2.2).

Table 2.2: Examples of rule inference using regression

Regression procedure	Examples
Linear regression	Bhaskar and Whitlatch (1980); Karamouz et al. (1992); Karamouz and Houck (1987, 1982); Loucks (1970); Ostadrahimi et al. (2012); Young (1967)
Nonlinear regression	Bhaskar and Whitlatch (1980); Celeste et al. (2009); Celeste and Billib (2009)
Piecewise linear regression	Huang et al. (2016); Lund (1996); Lund and Ferreira (1996); Pulido-Velazquez et al. (2004)
Fuzzy regression	Malekmohammadi et al. (2009); Mousavi et al. (2007)
Support vector regression	Aboutalebi et al. (2015); Ji et al. (2014)

Interpolation

Interpolation defines operating rules based on the results obtained at some specific points, extending them to the whole state space of the explanatory variables. The resulting operating rules consist of a set of mathematical functions defined using the available points as boundary conditions. This maintenance of the given values is the main advantage of interpolation, as well as a better representation of the variability observed across the space of the explanatory variables (Celeste et al., 2009). On the other hand, the mathematical representation obtained is usually complex, since each region between neighboring points needs its own equation.

The most common interpolation equations are the piecewise linear and the piecewise cubic (also known as cubic splines). Interpolation is mainly used in conjunction with discrete dynamic programming or stochastic dynamic programming, to extend their results to the whole state space. In this way, it reduces the need of finer discretizations of the state variables, alleviating the curse of dimensionality (Celeste et al., 2009; Davidsen et al., 2015; Goor, 2010; Johnson et al., 1993; Nandalal and Bogardi, 2007; Tejada-Guibert et al., 1993).

Data mining

This technique efficiently analyzes large data sets to discover their hidden patterns or trends (Bessler et al., 2003), as well as which state variables are the most relevant drivers of decision-making (Hejazi and Cai, 2009). Instead of using a pre-set of candidates, data mining finds out the variables that should be taken into account in the definition of operating rules (Hejazi and Cai, 2011). Data mining can be used jointly with regression equations (Bessler et al., 2003) or as a pre-analysis technique (Hejazi and Cai, 2009; Soleimani et al., 2016) to ensure an adequate variable selection.

Rules-of-thumb

Rules-of-thumb are based on conceptual or mathematical deductions, experience and engineering principles (Lund, 1996; Lund et al., 2017; Lund and Guzman, 1999). These rules can be defined for diverse reservoir configurations, in series or in parallel, and for different operating purposes (Table 2.3, based on the comprehensive review by Lund et al., 2017).

Although each rule form possesses its own advantages and drawbacks, all of them have in favor a conceptually simple definition and the confidence that system operators have in them. Even some, as rule curves, appear in the regulatory frameworks of water resource systems (e.g. CHJ, 2013). Since their purpose is to guide system operators, they are usually used in real-life in conjunction with expert knowledge (Oliveira and Loucks, 1997). This need of additional specifications to map state variables to decisions is their primary disadvantage for their use in mathematical modeling.

Table 2.3: Main rules-of-thumb summary of applicability

Rule name	System types	Operating purposes
Standard Operating Policy (SOP)	Single reservoir	Water supply, flood control, navigation, environmental, recreation
Hedging rules (HR)	Single reservoir	Water supply, flood control, navigation, environmental, recreation
Pack rules (PR)	Single reservoir	Water supply, hydropower production
Rule curves	Single reservoir	Multiple purposes
Zone-based operation	Single reservoir	Multiple purposes
Water Storage Rules (WSR)	Reservoirs in series	Water supply, navigation, environmental, recreation
Flood Control Rules (FCR)	Reservoirs in series	Flood control
Hydropower rules	Reservoirs in series	Hydropower production
New York City Space Rule (NYCSR)	Reservoirs in parallel	Water supply, navigation, environmental, recreation
Equal Ratio Space Rule (ERSR)	Reservoirs in parallel	Water supply, navigation, environmental, recreation
Flood Control Space Rule (FCSR)	Reservoirs in parallel	Flood control

The form most used in research so far seems to be the rule curves (Celeste and Billib, 2009; Lerma et al., 2013; Wan et al., 2016). Classic rules for single reservoirs are the Standard Operating Policy (SOP) and, most common and efficient, hedging rules that reduce potential future severe shortages by reducing water deliveries when water availability is low (Lund and Draper, 2004; You and Cai, 2008).

Heuristic operating rules

The operation of complex multireservoir multipurpose water resource systems is likely to not be efficiently characterized using empirically-based rules or rules-of-thumb. This is because they would require complex fitting procedures ending sometimes in poor correlation coefficients (Labadie, 2004); or because they are beyond the applicability of rules-of-thumb (Lund et al., 2017). Heuristic procedures, on the other hand, are able to efficiently model the operation of complex water resource systems. They have grown in the last years favored by a continuous development of new methods and the rise of computation power. Each rule form possesses its own rationale behind, so they are quite different methods with regard to their behavior.

Artificial neural networks

Artificial neural networks (ANN) map input to output variables based on a mathematical process inspired by the human brain, in which simple units (neurons) are massively aggregated and interlinked to reproduce complex relationships (Fig. 2.2). Each neuron or node implements a single-input single-output function fed with a weighted sum of the inputs to the ANN or by outputs from previous layers (Labadie, 2004). Mathematical relationships can be modeled by establishing the number of nodes and how they are connected, as well as the functions and weights of each node.

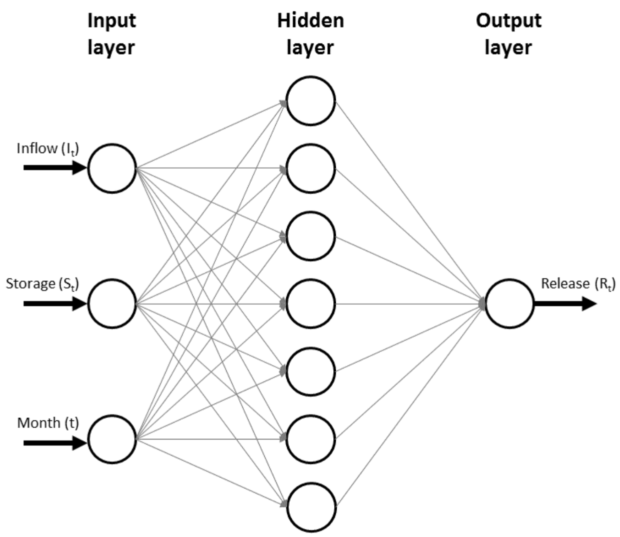


Fig. 2.2: Artificial neural network schematic

The advantages of an ANN are its ability to reproduce complex mathematical relationships and its high computational efficiency, reducing the computing power requirements in comparison with similar approaches (Cancelliere et al., 2002). Its main drawback is its marked heuristic character, since the equations and coefficients employed by an ANN do not correspond to the ones associated with the physical processes modeled. This issue makes ANNs to be seen as *black boxes* whose rationale is difficult to be understood by decision-makers not familiar with them, hindering its acceptability (Russell and Campbell, 1996).

ANNs have been applied in the assessment of optimal operating rules since the 90's with adequate results. Their performance has been found superior than equivalent regression procedures (Chandramouli and Raman, 2001; Raman and Chandramouli, 1996), rules-of-thumb (Cancelliere et al., 2002; Chandramouli and Raman, 2001; Liu et al., 2006) and interpolation from stochastic dynamic programming results (Giuliani et al., 2015; Raman and Chandramouli, 1996).

A derivative approach combining ANNs and fuzzy rule-based systems, named adaptive network-based fuzzy inference system (ANFIS), has been applied to define optimal operating rules with good results (Celeste and Billib, 2009; Chang and Chang, 2001; Mousavi et al., 2007).

Bayesian networks

Although their use in reservoir operating rules has been very limited so far, Bayesian networks have been widely applied in fields like system maintenance and medicine (Castelletti and Soncini-Sessa, 2007a). A Bayesian network has two components: a graphical representation of the logical relationships between variables, based on nodes and links, and a probabilistic model consisting of conditional probabilities attached to each link (Fig. 2.3) (Castelletti and Soncini-Sessa, 2007b). Input values enter the network at the root nodes (nodes without arriving links) and follow the links between them until the leaf nodes are found (nodes without departing links), whose values are the outputs. The distinctive features of Bayesian networks are that output values are given in the form of probability distribution functions and that inputs can be single values (certain) or probability functions (uncertain). In the latter, they are useful to aid in expert decision-making (Castelletti and Soncini-Sessa, 2007b).

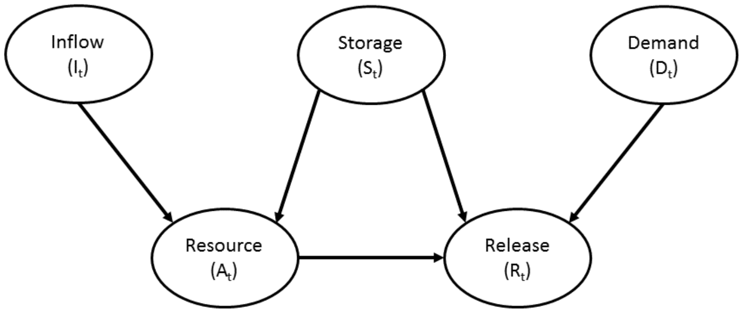


Fig. 2.3: Bayesian network schematic

Their main advantage is the ability to be understood by people not familiar with them, thanks to their explicit graphical representation. They are also efficient in mapping complex relationships while taking into account uncertainty (Malekmohammadi et al., 2009). However, they are not able to model multicomponent systems (like water resource systems) guaranteeing that every individual component would be accurately modelled. If used to represent part of a multicomponent system, the rest of it needs to be defined in a compatible way (Castelletti and Soncini-Sessa, 2007b). In spite of the few applications noticed in the field, they have been compared with regression procedures, to reproduce optimal operating rules, showing better results (Malekmohammadi et al., 2009).

Expert-knowledge based rules

Although heuristic methods are able to efficiently model complex operation procedures, they suffer a disadvantage: the rationale behind the processes they use may not be in line with the ones employed by system operators. This issue hampers the interaction with decision-makers, who feel more comfortable if they are involved in the development process (Labadie, 2004), as well as if the operating rule form is able to match the stages and criteria they use (Oliveira and Loucks, 1997).

These stages usually include comprehensive negotiation and subsequent agreements on how to operate the system. In this context, operating rules provide guidance to the system operators, but their judgment is still required 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).

To solve this issue, expert-knowledge based rules employ a flexible internal structure, which can be adapted to closely reproduce the decision-making processes, criteria and the rationale behind them. These methods are able to *capture* expert knowledge and combine it with other information sources (mainly historical records and optimization algorithms). They can also be used, in the absence of expert knowledge, as heuristic methods, offering in general similar performance levels than them.

Fuzzy rule-based systems

This procedure maps input to output variables using fuzzy logic (Mamdani, 1974; Zadeh, 1965). A fuzzy rule-based system consists of a set of logical rules expressed using IF-THEN sentences (fuzzy rules), in which the premises and/or the consequences are provided using fuzzy numbers and operated with fuzzy operators (Sen, 2010; Shrestha et al., 1996). The mapping process is known as fuzzy inference procedure. A comprehensive description of fuzzy logic is given later in subsection 2.2.1.

The main advantages of fuzzy rule-based systems are their efficiency in mapping explanatory variables to decisions in a flexible approach, closer to the way in which decisions are made (Moeini et al., 2011; Mousavi et al., 2005; Panigrahi and Mujumdar, 2000; Russell and Campbell, 1996; Yang and Ng, 2016), and their possibilities to combine numerical data with expert judgment (Macian-Sorribes and Pulido-Velazquez, 2017; Pedrycz et al., 2011). However, their concepts and quantifications may be perceived as strange and hostile in comparison with classical approaches in which system operators rely (Russell and Campbell, 1996; Sen, 2010). Furthermore, complex fuzzy rule-based systems may be cumbersome to work with due to an excessive number of rules (Sen, 2010).

Fuzzy logic has been applied, in the assessment of optimal operating rules for both single and multireservoir systems, in combination with deterministic (Mousavi et al., 2005; Senthil kumar et al., 2013; Yang and Ng, 2016) and stochastic optimization algorithms (Panigrahi and Mujumdar, 2000; Russell and Campbell, 1996). Several studies have compared this approach with interpolation (Moeini et al., 2011; Russell and Campbell, 1996) and regression (Mousavi et al., 2005). It has also been compared with other heuristic procedures such as ANNs and decision trees (Senthil kumar et al., 2013), as well as in situations subject to inflow non-stationarity and/or the existence of multiple objectives (Yang and Ng, 2016). More information about its applications can be found in subsection 2.2.1.

Decision trees

Decision trees are a knowledge discovery method, in which the patterns followed in decision-making processes are inferred from data sets (Wei and Hsu, 2008). As Bayesian networks, they represent operating rules through a graph consisting of nodes and arcs, although the calculation processes are significantly different. In a decision tree, each node represents an attribute or variable, while each arc corresponds to a situation applicable to it (like having certain values or being within a range). The input values enter the tree in the root nodes and are passed through the arcs to the terminal nodes. Each path followed across the tree represents a rule, and the values of the variables in the terminal nodes are the decisions attached to it.

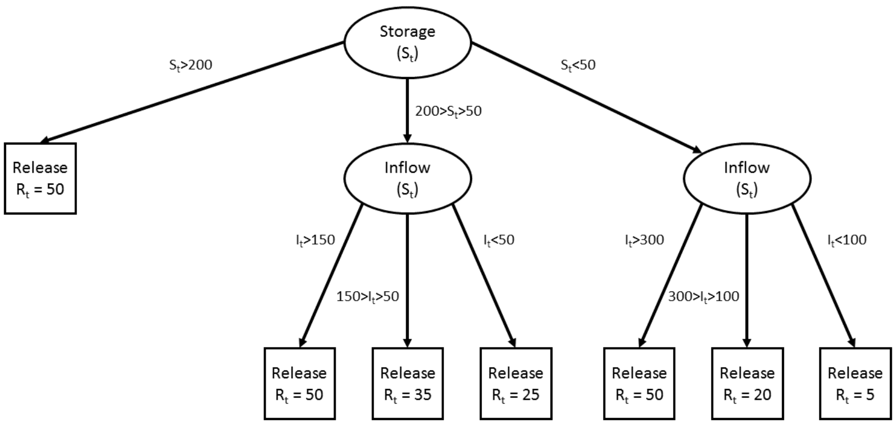


Fig. 2.4: Decision tree schematic

The main advantages of decision trees are their conceptual simplicity, their efficiency to handle large data sets and the fact that they can be easily complemented with expert knowledge (Wei and Hsu, 2008). Their main drawback is that each node is restricted to work with just one variable, so complex operating rules are likely to result in large cumbersome trees. In addition, they are not able to handle interdependent variables (Wei and Hsu, 2008). The main use of decision trees in water resources management corresponds to the forecasting of future inflows under the name of scenario trees (Castelletti et al., 2010; Chazarra et al., 2016; Côté and Leconte, 2015; Ficchì et al., 2015; Galelli et al., 2014; Housh et al., 2013). Optimal operating rules using decision trees have also been used in water resources management (Senthil kumar et al., 2013; Wei and Hsu, 2008). Their performance has been found to be similar to ANNs (Senthil kumar et al., 2013).

2.2. FUZZY LOGIC USE IN WATER RESOURCES MANAGEMENT

Pioneered by Zadeh (1965), the fuzzy set theory can be briefly described as an attempt to quantify vague (nonrandom uncertain) concepts, regarding their intuitive meaning, in a mathematical way that allows them to be operated and easily understood. Fuzzy logic is based on imprecise human reasoning, embedding it into complex problems in an effective way (Ross, 2010). As an example, concepts as *low*, *large*, *heavy*, etc., whose quantification regarding classic methodologies is challenging, can be easily expressed using fuzzy sets and then operated using fuzzy operations. In this way, fuzzy logic takes advantage of situations in which high precision is not required, being able to exploit our tolerance to imprecision (Ross, 2010). Comprehensive fuzzy set theory definitions and operation descriptions can be found in Simonovic (2009), Sen (2010), Ross (2010), and Macian-Sorribes (2012, in Spanish), as in a large number of related publications.

2.2.1. Fuzzy logic

Fuzzy logic (Mamdani, 1974) is the main derivative of the fuzzy set theory. It can be defined, as classic or Boolean logic, as a way to obtain output values based on inputs using logic rules in the form of IF-THEN sentences:

IF x is A and y is B, then z is C

The main difference between a Boolean rule and fuzzy rule is that the latter uses fuzzy sets in its premises. Considering the previous rule, both A, B and C would be fuzzy sets (or fuzzy numbers). These can be associated with linguistic descriptions like *low*, *normal* or *high*. Linking language with mathematics is the main advantage of fuzzy logic, since humans tend to feel more comfortable when using words (Sen, 2010). In consequence, people would feel more familiar with the description of a fuzzy rule than with its Boolean equivalent, in which the numbers sometimes hide the real meaning behind (Sen, 2010).

In addition, a fuzzy rule benefits from the fuzzy sets and numbers' ability to capture and treat the subjective uncertainty, also known as ambiguity, vagueness or fuzziness; being able to embed it, work with it and propagate it to further mathematical processes (Pedrycz et al., 2011; Simonovic, 2009). The use of fuzzy numbers to consider this uncertainty is not only beneficial in terms of estimating its effect in an efficient way (Simonovic, 2009), but also supposes a computational advantage, since fuzzy rule-based systems are able to reproduce complex mathematical relationships with a reduced number of fuzzy rules (Sen, 2010).

Another distinct feature of a fuzzy rule is that it is not restricted to the *to be or not to be* approach offered by Boolean logic, in which a rule can be either followed (logic value 1) or not followed (logic value 0). On the contrary, a fuzzy rule can be definitely followed (logic value 1), definitely not followed (logic value 0) or partially followed (logic value between 0 and 1). This partial membership to a concept is one of the reasons why the fuzzy set theory is close to the real world, in which the all-or-nothing approach hardly applies, but what matters is how much something is true or false (Pedrycz et al., 2011).

A fuzzy rule-based (FRB) system, also known as fuzzy inference system (FIS) or fuzzy logic system, is a set of fuzzy rules put together with the fuzzy numbers that quantify the rules' premises and consequences, and diverse fuzzy operators that are required to link inputs with outputs. In order to create a fuzzy rule-based system, several stages are needed, being explained in the following section.

According to how are they built and operated, there are two main types of fuzzy rule-based systems: Mamdani and Sugeno. Other kinds of FRB systems have been developed although little applied in comparison (Sen, 2010). The main distinctive feature of a Mamdani FIS (Mamdani, 1974) is that it uses both fuzzy inputs and outputs, so the results of the inference process are expressed as fuzzy sets. This type of fuzzy inference is the most popular one when building a FRB system (Sen, 2010). On the other hand, a Sugeno FIS (Sugeno, 1985), considers mathematical equations as the outputs of the FRB system. Despite these differences, the rationale behind the building and inference processes remains the same, as well as the majority of the mathematical procedures required (Sen, 2010).

Fuzzy rule-based systems building

The following description on how to build a fuzzy rule-based (FRB) system is based on the research carried out by Bai and Tamjis (2004); Campbell (1993); Dubrovin et al. (2002); Mousavi et al. (2005); Panigrahi and Mujumdar (2000); Russell and Campbell (1996); and Shrestha et al. (1996). Although these works (and others) introduced custom features to adapt the methodology to the application, the process remains almost the same (Fig. 2.5). Since the following description focuses on building FRB systems for water resources management, it contains some of the modifications made to adapt the process to the specific needs of the field (Dubrovin et al., 2002; Russell and Campbell, 1996; Shrestha et al., 1996).

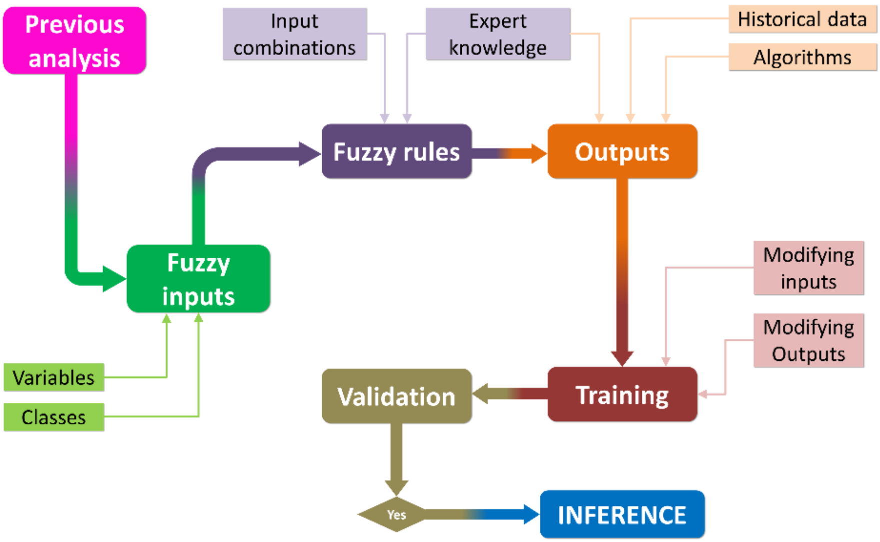


Fig. 2.5: FRB System building flowchart

Previous analysis

Since fuzzy logic works with linguistic variables based on human reasoning, it is necessary to find out what relationships exist in the water resource system analyzed (Sen, 2010). The previous analysis should not only focus on data and information collection, but on acquiring expert knowledge to blueprint the relationships found between state and decision variables. This will frame the FRB main features and goals.

Fuzzy inputs

This stage can be subdivided into two: input definition and input characterization. The first refers to choosing the input variables. Typical variables used in water resource systems are initial storage, inflows, time of the year, rainfall and so on (Dubrovin et al., 2002; Panigrahi and Mujumdar, 2000; Sen, 2010; Shrestha et al., 1996). Once decided, the input variables should be characterized using different linguistic descriptors like *low*, *excessive*, *rather good*, *extremely advantageous* and so on (Bai and Tamjis, 2007; Russell and Campbell, 1996).

Examples on how to linguistically characterize a variable can be found in Pedrycz et al. (2011); and Sen (2010). To complete the characterization, a fuzzy number should be attached to each descriptor. These numbers can be determined using a systematic approach (Russell and Campbell, 1996), historical data (Shrestha et al., 1996), expert knowledge (Pedrycz et al., 2011; Sen, 2010) and combinations between them (Dubrovin et al., 2002; Panigrahi and Mujumdar, 2000).

Fuzzy rules

Fuzzy rules are formed by combining inputs, and characterized creating IF-THEN sentences like: *if storage is* low *and inflow is* high*, then release is …* If every combination between linguistic descriptors is possible, the number of rules is equal to the product of the number of linguistic descriptors (e.g.: a FRB system with two inputs with 5 and 6 linguistic descriptors would possess 30 fuzzy rules).

Although fuzzy rules with the *and* logical operator are usually the ones employed in water resources management (Russell and Campbell, 1996; Shrestha et al., 1996), it is possible to define them with other logical operators. It is also possible, although not common, to define fuzzy rules with different numbers of variables (Sen, 2010).

Outputs

Output definition requires to state the number of output variables and to quantify them. Typical outputs in FRB systems for water resources management are releases (Shrestha et al., 1996) and the target storage (Russell and Campbell, 1996). Outputs can be characterized by either fuzzy (Bai and Tamjis, 2007; Dubrovin et al., 2002; Panigrahi and Mujumdar, 2000; Shrestha et al., 1996) or non-fuzzy numbers (Mousavi et al., 2005; Russell and Campbell, 1996).

Fuzzy outputs represent a Mamdani FIS while non-fuzzy ones are associated with a Sugeno FIS. They can be quantified by using historical data (Bai and Tamjis, 2007; Dubrovin et al., 2002; Shrestha et al., 1996), mathematical algorithms (Mousavi et al., 2005; Panigrahi and Mujumdar, 2000; Russell and Campbell, 1996) and expert knowledge (Sen, 2010).

Training

The training or calibration stage consists in modifying the response of the FRB system in order to adapt it to the desired behavior. The training of a FRB system can be done theoretically in two ways: modifying the inputs and/or modifying the outputs. Nonetheless, the vast majority of FRB developments have relied on modifying the outputs (Bai and Tamjis, 2007; Dubrovin et al., 2002; Sen, 2010; Shrestha et al., 1996). Varying the output values is definitely simpler than doing the same with the inputs. Furthermore, inputs may be characterized taking into account expert knowledge (Dubrovin et al., 2002; Panigrahi and Mujumdar, 2000) that would be lost if they were modified during the fitting process.

Validation

Validation consists in contrasting the performance of the FRB system using data not employed in the training process. In this case, if the performance level is not adequate, the FRB building process needs to be restarted. If it is successful, then the FRB system created is considered as valid and can be used in further analyses or developments.

The fuzzy inference procedure

The fuzzy inference procedure maps inputs to outputs for each time stage of the analysis period (Fig. 2.6). It corresponds to the stage in which the validated FRB system is used to reproduce the mathematical relationship between inputs and outputs. A detailed description of this process can be found in Bai and Tamjis (2007); Macian-Sorribes (2012, in Spanish); Panigrahi and Mujumdar (2000); and Sen (2010).

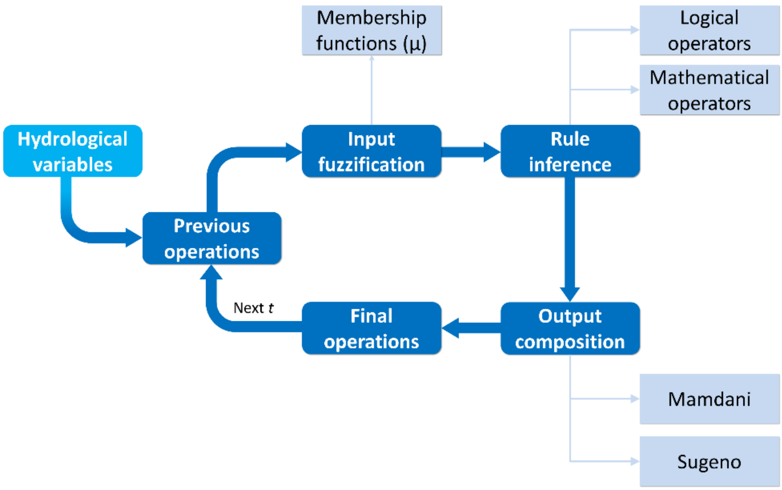


Fig. 2.6: Fuzzy inference flowchart

Previous operations

This first stage consists in obtaining the input variables based on the data sets available. It is not necessary if the available information already fits the input variables. Typical situations when previous operations are required refer to FRB systems that use forecasted variables (Shrestha et al., 1996), as they must be obtained prior to the inference.

Input fuzzification

In the fuzzification stage, the input values are introduced into the FRB system by computing how they match the different linguistic categories. This calculation is done using the fuzzy numbers attached to each descriptor. It consists in obtaining the degree of membership that represents how much the input belongs to the given fuzzy number (Bai and Tamjis, 2007; Panigrahi and Mujumdar, 2000; Sen, 2010).

Rule inference

This process uses the results of the fuzzification to determine the extent to which each fuzzy rule is true. For each end every rule, the degrees of membership associated with its inputs are combined in order to obtain a single numerical value that expresses how certain is this rule given the inputs. This value, known as degree of fulfillment (DOF, Shrestha et al. 1996), can be calculated by two main ways:

- Using logical operators (Bai and Tamjis, 2007; Panigrahi and Mujumdar, 2000; Sen, 2010).
- Using mathematical operators like the product (Shrestha et al., 1996), or the squared product (Russell and Campbell, 1996).

The DOF is used in a Mamdani FIS to modify the fuzzy outputs. This operation, also known as implication, usually consists in truncating (Bai and Tamjis, 2007; Panigrahi and Mujumdar, 2000; Sen, 2010) or re-scaling (Sen, 2010) the fuzzy outputs to reflect the effect of partially-followed rules. A Sugeno FIS does not require additional operations after its calculus.

Output composition

In this stage, the global outputs of the FRB system are assessed using the outcomes of the previous stage. In a Mamdani FIS, the fuzzy outputs modified in the rule inference are combined. This combination is usually done using logical operators (Sen, 2010). Once the global fuzzy outputs have been combined, a defuzzification operator should be applied if non-fuzzy responses are desired. In order to do so, several procedures have been used like the centroid, the mean of maxima and so on (Sen, 2010). In case of using a Sugeno FIS, the output composition process is easier as the outputs of each rule are already non-fuzzy numbers. The most used operation in this case is a weighted average in which the weights are the degrees of fulfillment (Russell and Campbell, 1996; Sen, 2010).

Final operations

The final operations consist in using the outputs of the FRB system in further calculations if desired. For this, the FRB system could be combined with a water resources management model that is executed after the inference process (Macian-Sorribes and Pulido-Velazquez, 2015). In these case, this model could also be used to compute the input variables for the following time stage.

Main applications in water resources management

In the water resources management field, fuzzy logic has been widely applied, following different purposes and reproducing various mathematical processes.

Development of reservoir operating rules

Including expert judgment in the definition of operating rules is the main advantage of fuzzy logic when used to represent reservoir management rules, as explicitly indicated in the published research (Bai and Tamjis, 2007; Macian-Sorribes and Pulido-Velazquez, 2017; Mousavi et al., 2005; Panigrahi and Mujumdar, 2000; Russell and Campbell, 1996; Sen, 2010; Shrestha et al., 1996). Furthermore, it has proven its suitability to mimic the desired behavior (Labadie, 2004; Rani and Moreira, 2010).

FRB systems have been applied to reproduce the current operating rules or to represent an optimal operation. Research focused on mimicking the historical behavior used FRB systems whose structure was built with the aid of expert judgment (Bai and Tamjis, 2007; Dubrovin et al., 2002; Macian-Sorribes and Pulido-Velazquez, 2017; Sen, 2010; Shrestha et al., 1996). These FRB systems were trained and validated against historical records (Dubrovin et al., 2002; Macian-Sorribes and Pulido-Velazquez, 2017; Sen, 2010; Shrestha et al., 1996).

When used to represent optimal rules, FRB systems aim at reproducing the decisions obtained by an optimization algorithm (Mousavi et al., 2005; Panigrahi and Mujumdar, 2000; Russell and Campbell, 1996; Senthil kumar et al., 2013; Yang and Ng, 2016). Expert knowledge could still be employed to set up the structure of the FRB system. Examples of using fuzzy logic to reproduce optimal operating rules regard to employing them in isolation (Moeini et al., 2011; Mousavi et al., 2005; Panigrahi and Mujumdar, 2000; Russell and Campbell, 1996; Senthil kumar et al., 2013; Yang and Ng, 2016) or in combination with ANNs within the ANFIS framework (Celeste and Billib, 2009; Chang and Chang, 2001; Mehta and Jain, 2009; Mousavi et al., 2007; Soltani et al., 2010). The ANFIS procedure is, by definition, more flexible than using the FRB in isolation (since its parameters are estimated by an ANN rather than being fixed) but, on the contrary, it increases the complexity of the process and thus hinders its understandability.

Demand forecasting

As regression, fuzzy logic can be used to forecast variables in response to present or past measurements of explanatory variables. Its main advantage with respect to statistical regression regards to its ability to efficiently represent complex mathematical relationships (Sen, 2010), a feature shared between fuzzy logic and ANNs (Labadie, 2004). Examples can be found for both urban and agricultural uses (Firat et al., 2009; Pulido-Calvo and Gutierrez-Estrada, 2009; Sen, 2010).

FRB systems have been used in isolation (Firat et al., 2009; Sen, 2010) or in conjunction with other methodologies. Firat et al. (2009) compared the performance of FRB and ANFIS methods. Differently, Pulido-Calvo and Gutierrez-Estrada (2009) used an ANN trained by a genetic algorithm to obtain the inputs of a FRB system whose goal was to forecast irrigation demands.

Hydrology

Hydrological phenomena are subject to complex non-linear relationships and a considerable amount of uncertainty and vagueness, something that can be efficiently handled with methods such as fuzzy logic (Sen, 2010). Fuzzy logic is also able to take advantage of expert knowledge. FRB systems have been applied in many ways within hydrology (Table 2.4).

Table 2.4: Fuzzy logic applications in hydrology

Application or goal	Examples
Development of hydrological models	FRB systems (Sen, 2010; Turan and Yurdusev, 2016) and ANFIS (Safavi et al., 2015)
Forecast of river discharges	Jayawardena et al. (2014); Sen (2010)
Hydrograph estimation combining FRB and ANFIS	Güçlü and Şen (2016)
Drought prediction	Pesti et al. (1996)
Estimation of hydrological variables (evaporation, infiltration, etc.)	Selim Güçlü et al. (2016); Sen (2010)
Water budget definition	Sen (2010)

Hydrogeology

Fuzzy logic applicability in hydrology can also be extended to hydrogeology. FRB systems have been used to approximate conjunctive use allocation (Chang et al., 2013), as well as for the estimation of groundwater recharge rates based on rainfall amounts (Sen, 2010). It has also been employed to classify aquifers according to its geological properties (Sen, 2010).

Other applications

Fuzzy logic has been used with other water-related purposes than the ones previously mentioned.

Table 2.5: Other fuzzy logic applications in water science

Application or goal	Examples
Water quality simulation with FRB or ANFIS	Soltani et al. (2010)
Water quality indexes assessment with FRB or ANFIS	Lermontov et al.(2009)
Environmental rehabilitation operations	Tzionas et al. (2004)
Investment ranking	Karnib (2004)
River dike and sewer pipe design	Vucetic and Simonovic (2011)

2.2.2. Fuzzy regression

Fuzzy regression can be described as a regression whose coefficients are fuzzy. It emerged as an alternative to statistical regression in the case of having imprecise variables, imprecise relationships and scarce or inaccurate data (Bardossy et al., 1990). Fuzzy regression these imprecisions within its structure via fuzzy parameters (Mousavi et al., 2007; Simonovic, 2009).

Its main advantage is its ability to work with few data records, something unattainable with statistical regression (Bardossy et al., 1990; Kim et al., 1996). In this case, fuzzy regression is able to capture non-random uncertainty in a simple way (Simonovic, 2009). The applicability of fuzzy regression in water resources management and hydrology regards to the fact that they are two science fields in which data can be scarce and/or inaccurate (Bardossy et al., 1990; Mousavi et al., 2007). However, the decision on the method to be used is case-dependent (Kim et al., 1996).

Formulation

Fuzzy regression can be formulated as the standard one but replacing its coefficients by fuzzy numbers (Eq. 2.5, based on Bardossy et al. 1990):

$$\tilde{y} = f(x, \tilde{c}) \tag{2.5}$$

In which $\tilde{y}$ dependent variable or output (fuzzy), f functional form, x vector of independent variables or inputs (fuzzy or non-fuzzy) and $\tilde{c}$ vector of parameters. In the case of a linear regression, Eq. 2.5 turns into:

$$\tilde{y} = \sum_i \tilde{c_i} x_i \tag{2.6}$$

In which *i* number of independent variables and coefficients.

To fit a fuzzy regression equation, it is needed to estimate the fuzzy coefficients through an optimization problem. Among the wide range of forms available (e.g. trapezoidal), the most straightforward way is to consider the coefficients as L-R fuzzy numbers (Bardossy et al., 1990), or symmetric triangular fuzzy numbers (Simonovic, 2009). The goal of the problem is to minimize the vagueness of the predicted output for a given degree of acceptability. In contrast with statistical regression, its performance level is predefined (the degree of acceptability).

In order to measure the vagueness of the regression, labeled as *V*, a measurement or vagueness criteria must be set (Bardossy et al., 1990; Mousavi et al., 2007; Simonovic, 2009). There are three main vagueness criteria available (Bardossy et al., 1990):

- The maximal vagueness of the fuzzy coefficients, or maximum width (interval in which the membership value is non-zero) among the $\tilde{c}_i$ coefficients.
- The average vagueness, or average width of the $\tilde{c}_i$ coefficients.
- The prediction vagueness, which is the vagueness provided by the fuzzy regression equation on the domain of the independent variables.

The degree of acceptability, labeled as *h*, establishes the minimum quality that the regression must possess. It is measured by comparing the fuzzy predicted output value with the fuzzy or non-fuzzy measured output (Bardossy et al., 1990; Mousavi et al., 2007; Simonovic, 2009).

- For fuzzy measured output values (Fig. 2.7 left), the regression is considered valid if, for each and every fuzzy measurement, the *α-cut* of level *h* of the measured output (O_1-O_2) is within the predicted one (P_1-P_2) (Bardossy et al., 1990).
- For non-fuzzy measured output values (Fig. 2.7 right), the regression offers an adequate performance if each and every measured output belongs to its corresponding fuzzy prediction with a membership degree *α* equal or higher than *h* (Simonovic, 2009).

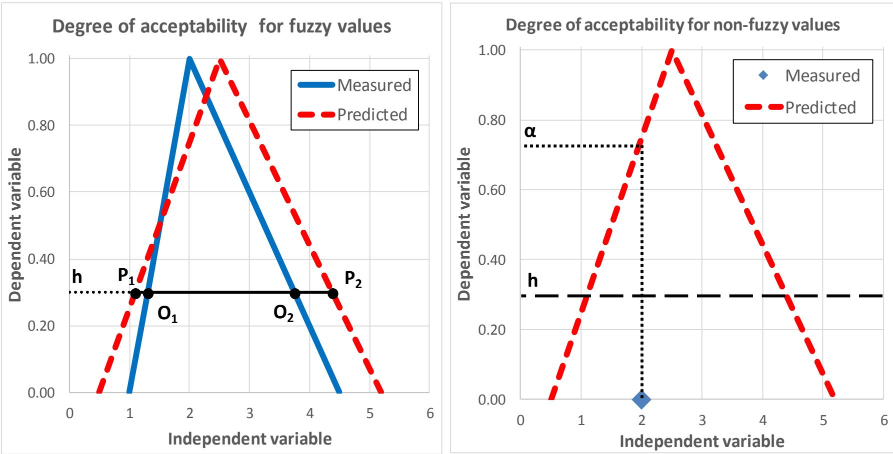


Fig. 2.7: Degree of acceptability criterion for fuzzy (left) and non-fuzzy (right) output measurements

Consequently, the optimization problem can be defined as:

$$Minimize\, V(\tilde{c})$$

$$Subject\ to:$$

$$\begin{aligned} &\tilde{y}_j = f(x_j, \tilde{c}) \quad for\ each\ record\ j \\ &V = vagueness\ criterion\ equation \\ &Each\ \tilde{y}_j\ complies\ acceptability\ with\ level\ h \end{aligned} \qquad \textbf{2.7}$$

Initially the process described was defined for symmetric fuzzy coefficients (Bardossy et al., 1990; Kim et al., 1996; Simonovic, 2009). It was extended to asymmetric fuzzy numbers by Ishibuchi and Nii (2001), who modified the procedure described above to fit separately the width of the fuzzy coefficients and their modal values, using a least-squares regression to fit the latter. Alternative fitting approaches, such as hybrid least-squares regression (Chang, 2001) have also been developed.

Main applications in water resources management

As statistical regression, fuzzy regression has been applied in both water resources management and hydrology. It is applicable to situations in which fuzzy regression is a suitable alternative to statistical regression due to the features mentioned above.

Although not extensively used, its main application in water resources management has been the definition of reservoir operating rules as an alternative to statistical regression. Mousavi et al. (2007) used fuzzy regression to estimate optimal operating rules for both the long and the medium-term operation of a reservoir. Deterministic dynamic programming was used to obtain the data records employed in the fitting process. Fuzzy regression was compared with statistical regression and ANFIS-based rules. They found out that the operating rules generated by fuzzy regression outperformed statistical regression in both the long and the medium-term, and even ANFIS in the long-term. They pointed out that fuzzy regression was especially adequate when data availability was reduced.

Similarly, Malekmohammadi et al. (2009) applied fuzzy regression to obtain optimal reservoir operating rules for a two-reservoir system, comparing it with Bayesian networks and statistical regression. Optimization results obtained from a genetic algorithm were used in the fitting process. Their results showed that fuzzy regression outperformed statistical regression in both the fitting and the performance quality, but was overwhelmed by the fitted Bayesian network.

Zahraie and Hosseini (2009) employed fuzzy regression to assess optimal operating rules including variations in demands. A genetic algorithm was used to derive the data sets for the fitting process. Both symmetric and asymmetric fuzzy regressions were employed, as well as different combinations of independent variables. The procedure was tested in a single reservoir system. They found out that fuzzy regression outperformed statistical regression, with asymmetric coefficients offering higher efficiency levels. They concluded that fuzzy regression was a proper way to accommodate the uncertainty on future demands on the operating rules.

Fuzzy regression has also been applied in hydrology. It has been used in the estimation of the soil hydraulic permeability (Bardossy et al., 1990), in the estimation of fuzzy hydrological parameters (Ozelkan and Duckstein, 2001) and in the approximation of stage-discharge curves (R. Shrestha and Simonovic, 2009; R. R. Shrestha and Simonovic, 2009), among other goals.

2.2.3. Modeling expert knowledge in fuzzy logic

Fuzzy logic is said to efficiently integrate expert knowledge in mathematical modeling. Its treatment of the uncertainty and fuzziness associated with mathematical measurements through membership functions, and its use of linguistic variables, make it closer to human reasoning than the classic Boolean logic (Pedrycz et al., 2011; Sen, 2010). This resemblance with human thinking makes it understandable by people, being possible to mathematically express their thoughts, opinions and knowledge (Zadeh, 2008). In a FRB system, expert judgment can be included in two main ways:

- In the FRB structure (number of inputs, number of outputs and number and features of the rules).
- In the membership functions of the input and/or output quantifications.

Expert knowledge in the FRB structure

This type of expert knowledge inclusion consists in taking expert judgment into account when determining which variables will be the inputs of a FRB system and which output variables will be obtained, as well as the number and premises of the fuzzy rules. With regard to inputs and outputs, expert knowledge is considered when the decisions of which variables will be used are made on the basis of expert judgment (Gurocak and Whittlesey, 1998; Karnib, 2004; Sen, 2010; Tzionas et al., 2004).

For example, one can set a FRB system for defining a reservoir's operating rules, without further knowledge on how it is operated, using as inputs the current inflow forecast, the initial storage level and the month of the year. However, in case of a reservoir devoted exclusively to urban demands or industrial users, whose temporal variability is negligible or limited, the month of the year could be eliminated. In this situation, the use of expert judgment would result in an efficiency increase due to less input variables.

This input and output choice by expert judgment is also shared by other methodologies such as regression, decision tress and Bayesian networks. In fact, its ability to be adapted to expert judgment is one of the main advantages of these techniques (for example, see Castelletti and Soncini-Sessa, 2007b, for Bayesian networks). Mathematical and/or statistical analyses can be used to support, compare and contrast experts' opinion.

With regard to the number of fuzzy rules, expert judgment is used when they are asked about the characterization of the fuzzy rules by combining inputs. In fact, expert view is one of the ways in which the fuzzy rules are established (Sen, 2010). As the input and output choice, expert knowledge on the system modeled by the FRB would result in a more efficient representation. Clustering analyses can be used to support, compare and contrast expert knowledge (Pedrycz et al., 2011; Sen, 2010).

This feature is shared with other methodologies in which the input variables are divided in intervals, such as Boolean logic systems or decision trees. However, fuzzy logic possesses one advantage over them, which is the use of linguistic descriptors such as *low*, *extremely* or *insufficient*. This feature enables the acquisition of expert knowledge in a more efficient way, giving importance to the concept rather than to its exact quantification.

Expert knowledge in the membership functions

Including expert knowledge in the membership functions is an exclusive feature possessed by fuzzy logic. Given that fuzzy numbers can be mathematically operated as if were non-fuzzy ones, the membership function elicitation using expert judgment allows its introduction in any mathematical process. Such a feature opens a wide range of possibilities to work with expert knowledge in fuzzy logic.

It is said that expert judgment is used in membership function estimation when one employs the information given by them to build the fuzzy numbers (Pedrycz et al., 2011; Sen, 2010; Simonovic, 2009). Differently from the previous ways to take into account expert judgment, its consideration in membership function elicitation is not straightforward: we could not directly ask an expert about membership function estimation unless he or she is an expert in fuzzy logic too. Consequently, there are some methods with which their judgment is transformed into membership functions.

These methodologies can be divided between direct and indirect methods (Simonovic, 2009). A comprehensive description of them is given in Pedrycz et al. (2011). The ones considered in this thesis have been the horizontal and the vertical method. The main reasons why they have been chosen are their simplicity and their efficiency in generating membership functions accurate enough to be employed in a FRB system. In situations in which more accurate descriptions of membership functions are needed (such as fuzzy optimization), more sophisticated methods would be required.

The horizontal method

The horizontal method is recommended when a large number of experts can be involved in the membership function estimation. In this method, a sample of *x* values is chosen from the domain of variable *X* whose membership functions are desired. Then, for each value of *x* and each one of the linguistic variables *A* in which *X* has been divided (e.g. *low*, *medium* and *high*), a question like the following is asked (Pedrycz et al., 2011):

Can be x considered as A?

For which the answer should be *yes* or *no*. Once all the experts are asked, the membership degree of *A* for each value *x* is the number of experts who answered *yes* divided by their total number (Pedrycz et al., 2011). Then, interpolation procedures can be used to obtain the membership function for the whole domain of *X*.

For example, consider a reservoir of 500 Mm^3. Three linguistic descriptors have been attached to its storage (*low*, *medium* and *high*). The following sample has been chosen: *{0, 100, 200, 300, 400, 500}*. Twenty experts where asked, for each and every sampled value, if it could be considered as a *low*, *medium* or *large* storage level (Table 2.6). The number of positive answers defined the membership degree at each of the sampled points. Piecewise linear interpolation was then applied to determine the membership functions for the whole domain (Fig. 2.8). The method, as well its advantages and drawbacks, is comprehensively described in Pedrycz et al. (2011).

Table 2.6: Example of membership function elicitation using the horizontal method

Expert answers and membership degrees	Sampled values					
	0 Mm³	100 Mm³	200 Mm³	300 Mm³	400 Mm³	500 Mm³
Answered yes to *low* storage	20	20	12	2	0	0
Answered yes to *medium* storage	0	7	15	20	9	0
Answered yes to *high* storage	0	0	0	8	17	20
Memberships for *low* storage	1.00	1.00	0.60	0.10	0.00	0.00
Memberships for *medium* storage	0.00	0.35	0.75	1.00	0.45	0.00
Memberships for *high* storage	0.00	0.00	0.00	0.40	0.85	1.00

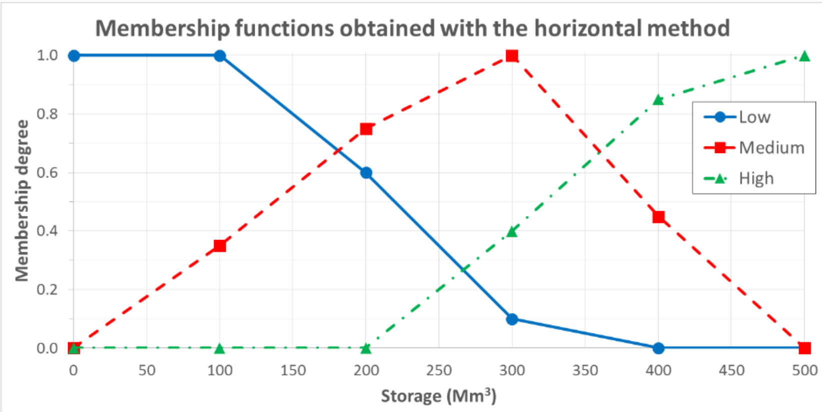


Fig. 2.8: Example of membership function elicitation using the horizontal method

The vertical method

The vertical method is adequate in situations in which the number of experts is reduced. In this method, different membership degrees or *α-levels* are considered and each expert is asked a question like the following (Pedrycz et al., 2011):

Which elements of X can be considered as A at degree no lower than α?

For a specific category *A*, the interval associated with each *α-level* is one *α-cut* of the corresponding fuzzy number. The responses obtained by each expert should be combined into a single set of *α-cuts* by mathematical operations (average interval, union of responses, intersection of responses and so on). Alternatively, experts can be asked to provide a single set of *α-*

cuts if they can reach consensus. The combination of the resulting *α-cuts* corresponds to the fuzzy number.

Consider the same example as for the horizontal method. Five *α-levels* have been defined: *{0.00, 0.25, 0.50, 0.75, 1.00}*. However, assume that, in this case, only five experts where available, so we were able to gather them together and let them discuss and agree in a single set of *α-cuts* (Table 2.7). These are obtained for low, medium and high storage levels. The resulting *α-cuts* were used to build the fuzzy numbers representing a *low*, a *medium* and a *high* storage level. The method, as well its advantages and drawbacks, is comprehensively described in Pedrycz et al. (2011).

Table 2.7: Example of membership function elicitation using the vertical method

Reservoir category	Intervals (Mm^3)				
	α=0.00	α=0.25	α=0.50	α=0.75	α=1.00
Low	0 to 200	0 to 175	0 to 150	0 to 75	0 to 50
Medium	100 to 400	125 to 350	150 to 325	200 to 300	225 to 275
High	250 to 500	300 to 500	350 to 500	400 to 500	450 to 500

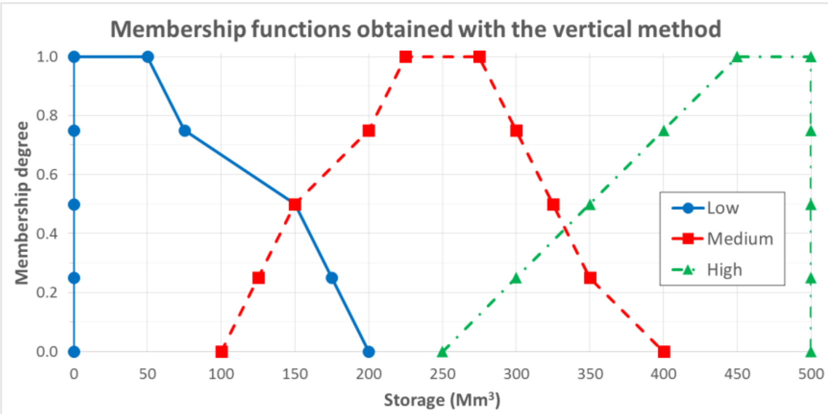


Fig. 2.9: Example of membership function elicitation using the vertical method

Applications in water resources management

The applications in water science in which fuzzy set theory and fuzzy logic were used explicitly to elicit expert knowledge regard to different fields and diverse goals. Given that expert judgment is usually used, to some extent, in fuzzy set theory or fuzzy logic, the applications described here correspond solely to situations in which expert judgment was clearly the main or the unique source of information. Most of them regard to the elicitation of membership functions. They offer a way to measure the acceptability of a variable in response to a specific need or problem (e.g. a membership function representing *adequate storages* would have higher membership degrees for the most desired storage values and lower ones for undesired ones).

Fuzzy membership functions built on the basis of expert judgment have been used in optimization algorithms to provide a unified metric for ranking management decisions concerning multiple objectives (Fontane et al., 1997; Kindler, 1992; Tilmant et al., 2007, 2002a, 2002c). Membership functions were estimated for the different goals of reservoir management, being combined through fuzzy arithmetic operations and included in an optimization algorithm to attain the best possible membership degree. This process has been employed in both deterministic (Fontane et al., 1997; Kindler, 1992; Tilmant et al., 2007, 2002a, 2002c) and stochastic optimization (Fontane et al., 1997; Kindler, 1992; Tilmant et al., 2007, 2002a, 2002c).

A similar approach used fuzzy set theory and fuzzy logic in multicriteria decision analysis. Fuzzy membership functions were estimated based on expert judgment and then employed in multicriteria analysis algorithms (Bárdossy and Duckstein, 1992; Bender and Simonovic, 2000; Yin et al., 1999) or in a FRB system (Gurocak and Whittlesey, 1998; Tzionas et al., 2004).

Apart from decision-making applications, fuzzy set theory and logic have been used in situations in which expert knowledge was the only suitable source of information. In this case, membership functions based on expert knowledge were assessed and operated to find out the desired information. Some applications include the assessment of nitrate concentration in groundwater (Bardossy et al., 1993), evaluation of flood protection (Despic and Simonovic, 2000; Simonovic, 2009) and aquifer classification (Sen, 2010).

2.2.4. Other applications of fuzzy logic to water management

Apart from the ones previously presented, a wide range of techniques based on the fuzzy set theory have been applied in water resources management and hydrology. The existence of such a diverse set of possibilities is one of the main advantages of using fuzzy logic.

Fuzzy programming

Fuzzy programming seeks the maximum possible credibility or acceptability in a decision-making process subject to a set of constraints (Bellman and Zadeh, 1970). This acceptability is measured using membership functions that can be built using expert knowledge. Reviews of fuzzy programming can be found in Kacprzyk and Esogbue (1996); Liu and Esogbue (1996); Luhandjula (1989); and Sahinidis (2004). Applications in water resources management are included in Table 2.8.

Table 2.8: Fuzzy programming applications

Application or goal	Examples
Optimization of surface systems	Fontane et al., 1997; Kindler, 1992
Compromise optimization of groundwater systems	Bogardi et al., 1983
Multiobjective optimization of water resources management	Vucetic and Simonovic, 2011
Comparison with stochastic programming	Zeng et al., 2013
Optimization under water footprint constraints	Aviso et al., 2011
Determination of the optimal balance between economic and environmental performance	Lee and Chang, 2005
Modeling of climate change uncertainties	Teegavarapu, 2010
Allocation of water resources under uncertainty	Tsakiris and Spiliotis, 2004; Vucetic and Simonovic, 2011
Combination of fuzzy set theory and SDP to create fuzzy SDP	Mousavi et al., 2004a, 2004b; Rehana and Mujumdar, 2014; Tilmant et al., 2007, 2002a, 2002b, 2002c
Comparison between SDP and fuzzy SDP	Chandramouli and Nanduri, 2011; Tilmant et al., 2002c
Combination of probability and fuzzy set theory in SDP	Luhandjula, 2006; Luhandjula and Gupta, 1996
Fuzzy random variables in fuzzy optimization	Chen et al., 2015; Dong et al., 2014; Li et al., 2010; Li and Huang, 2009

Multicriteria decision analysis and making

Multicriteria decision analysis (MCDA) and multicriteria decision-making (MCDM) have been combined with fuzzy logic to take advantage of its unified metric and its possibilities to take into account expert knowledge. The resulting methodology was named as fuzzy multicriteria decision-making (Chen et al., 2011; Chiou et al., 2005), being reviewed by Pedrycz et al. (2011). Examples of its application can be found in Bárdossy and Duckstein (1992); Bender and Simonovic (2000); and Yin et al. (1999). Alternatively, fuzzy analytical network processes have been applied to rank watersheds in which to establish measures (RazaviToosi and Samani, 2016).

Fuzzy arithmetic

Fuzzy arithmetic has been widely applied in water resources management, mainly to take into account and propagate uncertainty through the calculation process, as well as to operate with the expert judgment mathematically embedded in the membership functions. Its main applications are summarized in Table 2.9.

Table 2.9: Fuzzy arithmetic applications

Application or goal	Examples
Flood control evaluation	Despic and Simonovic, 2000; Simonovic, 2009
Fuzzy performance indices	El-Baroudy and Simonovic, 2005, 2003, 2004; Fleming et al., 2014; Simonovic, 2009
Fuzzy conceptual hydrological models	Ozelkan and Duckstein, 2001
Analysis of urban water supply systems	Simonovic, 2009
Soil mapping under knowledge availability	Zhu et al., 2010

2.3. OPTIMIZATION OF LARGE WATER RESOURCE SYSTEMS INCLUDING STREAM-AQUIFER INTERACTION

Both deterministic and stochastic programming algorithms have been used to optimize large-scale water resource systems through a joint management of surface and groundwater resources, assuming a central and perfectly coordinated system operation.

Deterministic optimization models can handle complex conjunctive use optimization problems (e.g. Hanson et al., 2012; Jenkins et al., 2004; Marques et al., 2010; Pulido-Velazquez et al., 2006a, 2004; Reichard, 1995). The primary disadvantage of this approach is the perfect foresight. In contrast, stochastic optimization algorithms explicitly consider inflow uncertainty. They can be divided into two main areas: approaches in which uncertainty is handled by taking expectations on the future state of the system, and methods in which uncertainty is treated in a broader perspective. Within the latter one can mention the Info-Gap Decision Theory

(Ben-Haim, 2006) and Robust Optimization (Ben-Tal et al., 2009). Stochastic optimization algorithms, which make expectations on the future system state, often treat the problem as a single objective (often, maximization of expected benefits), fitting a probabilistic description to the inflow data. However, their use in large-scale water resource systems is hindered by the curse of dimensionality (Labadie, 2004). Tackling it down requires the use of aggregation-disaggregation techniques (Archibald et al., 1997) or derivative approaches.

In most reported applications of stochastic optimization to large-scale water resource systems, groundwater and stream-aquifer interaction processes are not explicitly modeled (Goor et al., 2010; Marques and Tilmant, 2013; Pereira and Pinto, 1991, 1985; Tilmant et al., 2008; Tilmant and Kelman, 2007) or are represented as underground reservoirs with no connection to surface waters (Davidsen et al., 2015, 2014; Marques et al., 2010; Zhu et al., 2015). However, in surface-groundwater systems, both components interact. In fact, groundwater abstractions can have a remarkable impact on surface resources with streamflow depletion due to groundwater overdraft (e.g. Barlow and Leake, 2012).

Stochastic Dual Dynamic Programming (SDDP, Pereira and Pinto, 1991, 1985) is one of the few stochastic alternatives for solving management problems in large-scale water resource systems. It has been used to derive optimal operating rules for multireservoir systems and to assess marginal water values (Goor et al., 2010; Marques and Tilmant, 2013; Tilmant et al., 2008; Tilmant and Kelman, 2007). This estimation of marginal water values is its distinct possibility. However, it is not able to mathematically represent stream-aquifer interactions. In order to make it applicable to large-scale water resource systems with reservoirs, aquifers and stream-aquifer interactions, SDDP needs to be extended. Part of the research of this thesis focuses on this issue.

2.4. DISCUSSION

Despite the wide range of optimization algorithms available, its efficiency in prescribing optimal decisions and the methodologies developed to derive operating rules based on their results, their use in the real-life operation of water resource systems has not increased as previewed, remaining a gap between theory and practice (Labadie, 2004; Maier et al., 2014; Rani and Moreira, 2010). The two main reasons behind this issue are:

1) Optimization models have intrinsic limitations that hinder their use in decision-making (Labadie, 2004; Rogers and Fiering, 1986). It should be taken into account that optimal decisions obtained by them are subject to the mathematical model of the system they assume. Reality is usually more complex than a mathematical model, so its results need to be adapted to the decision-making processes carried out in real-life.

2) Expert knowledge and criteria should be included in the definition of operating rules. Management decisions are usually the result of a process implying comprehensive negotiation and agreement reaching. Operating rules provide guidance to the system operators, but their expert knowledge is required in order to adapt the decisions previewed by the rules to the circumstances found at that time (Oliveira and Loucks, 1997). In fact, they sometimes deviate from the operating rules in response to specific conditions, objectives and constraints that may exist over time. Optimization models should take into account the decision-making processes carried out in the system (Maier et al., 2014).

These reasons are the main motivation of the research carried out in this PhD thesis. In order to develop operating rules based on optimization algorithms, ensuring they could be applied in real-life decision-making, expert criteria and knowledge should be combined with optimal decisions. Fuzzy logic, which has been proven to be able to embed expert judgment in its structure, is going to be used for this purpose. Optimization results will be provided by stochastic programming, in order to wipe out the perfect foresight associated with deterministic programming. However, stochastic programming algorithms developed so far did not explicitly model stream-aquifer interactions in large-scale water resource systems, thus requiring the development of new methods able to take it into account.

3. METHODS 1: STOCHASTIC OPTIMIZATION OF CONJUNCTIVE USE OF RESERVOIRS AND AQUIFERS IN LARGE WATER RESOURCE SYSTEMS[1]

The management of large water resource systems (with both several reservoirs and aquifers and in which surface and ground waters overlap) requires considering stream-aquifer interactions, as well as how they are affected by surface and groundwater management. Optimization models applied to large-scale systems have either employed deterministic optimization (with perfect foreknowledge of future inflows, which hinders their applicability to real-life operations) or stochastic programming (in which stream-aquifer interaction is often neglected due to the computational burden associated with these methods).

In this chapter it is presented the approach for the integration of stream-aquifer interaction in stochastic programming. It combines the Stochastic Dual Dynamic Programming (SDDP) algorithm with the Embedded Multireservoir Model (EMM). The resulting extension of the SDDP algorithm, named Combined Surface-Groundwater SDDP (CSG-SDDP), is able to properly represent the stream-aquifer interaction within stochastic optimization models of large-scale surface-groundwater resource systems.

3.1. OVERVIEW OF STOCHASTIC PROGRAMING

Stochastic programming has been chosen in this thesis due to its lack of perfect foreknowledge of future inflows. Since this issue becomes important in river basins subject to drought conditions (Rani and Moreira, 2010), as the Jucar River Basin, its further application to the case study is likely to produce more adequate results than deterministic formulations. Stochastic dynamic

[1] The methodology presented in this Chapter has been adapted from Macian-Sorribes et al., (2017). Its use complies with the Copyright Transfer Agreement signed between the authors and the American Geophysical Union (AGU)

programming combines dynamic programming with an explicit consideration of inflow uncertainty (Rani and Moreira, 2010). Its general objective function for optimal water resource system operations is (Stedinger et al., 1984):

$$F_t(s_t, q_{t-1}) = \max_{r_t} E_{q_t|q_{t-1}}[B_t(s_t, r_t, q_t) + F_{t+1}(s_{t+1}, q_t)] \qquad \textbf{3.1}$$

Were F_t total benefits between time stage t and the end of the planning horizon; s_t initial storage at time stage t; q_t inflows during time stage t; r_t decision (release or final storage) made; *E* expectation operator based on the conditional probability of q_t given q_{t-1}; B_t immediate benefits; and F_{t+1} benefits-to-go. In its standard formulation, the storage and the inflow variables are discretized and a Markov chain is used to characterize the uncertainty associated with future inflows given the current ones (Nandalal and Bogardi, 2007). These discretizations make it suffer the curse of dimensionality (Labadie, 2004; Rani and Moreira, 2010), requiring alternative stochastic programming approaches to deal with large-scale water resource systems.

In most of the research published on the stochastic optimization of large water resource systems, groundwater and stream-aquifer interactions were not explicitly modeled (Goor et al., 2010; Marques and Tilmant, 2013; Pereira and Pinto, 1991, 1985; Tilmant et al., 2008; Tilmant and Kelman, 2007), or aquifers were mathematically represented as underground reservoirs without any link with the surface system (Davidsen et al., 2015, 2014; Marques et al., 2010; Zhu et al., 2015). However, it is well-known that both components interact. In fact, groundwater exploitation can have remarkable impacts on the surface resources, reducing streamflows due to overdraft (e.g. Barlow and Leake, 2012).

Stochastic Dual Dynamic Programming (SDDP, Pereira and Pinto, 1991, 1985) is one of the alternatives developed to cope with the curse of dimensionality. It has been employed to derive optimal operation decisions for multireservoir systems and to assess marginal water values (Goor et al., 2010; Marques and Tilmant, 2013; Poorsepahy-Samian et al., 2016; Tilmant et al., 2008; Tilmant and Kelman, 2007). It has been chosen, among the set of SDP alternatives capable of handling large water resource systems, due to the long experience applications in complex water resource systems in which hydropower, agriculture and urban uses coexist (Rani and Moreira, 2010).

An extension of the SDDP algorithm has been developed to simulate the effect of stream-aquifer interactions in large-scale water resource systems. This extension has been named as *combined surface-groundwater stochastic dual dynamic programming* (CSG-SDDP, Macian-Sorribes et al., 2017). It incorporates a stream-aquifer interaction modeling procedure, the Embedded Multireservoir Model (EMM, Pulido-Velazquez et al. 2005), for the assessment of conjunctive water use strategies.

3.2. ONE-STAGE SUBPROBLEM BUILDING

The SDDP algorithm, and thus the CSG-SDDP one, optimizes the management of a water resource system applying the following objective function (Eq. 3.2), which is a version of the general one presented in Eq. 3.1.

$$F_t(s_t, q_{t-1}) = \max_{r_t} \; [B_t(s_t, r_t, q_t) + F_{t+1}] \qquad \textbf{3.2}$$

Where F_t total benefits obtained between time stage *t* and the end of the planning horizon; s_t system state at the beginning of time stage *t*; q_{t-1} inflows to the system at time stage *t-1*; B_t immediate benefits (the ones obtained in time stage *t*); r_t decision made in time stage *t*; q_t forecasted inflows during time stage *t* given the previous ones; and F_{t+1} benefit-to-go function represented as one scalar.

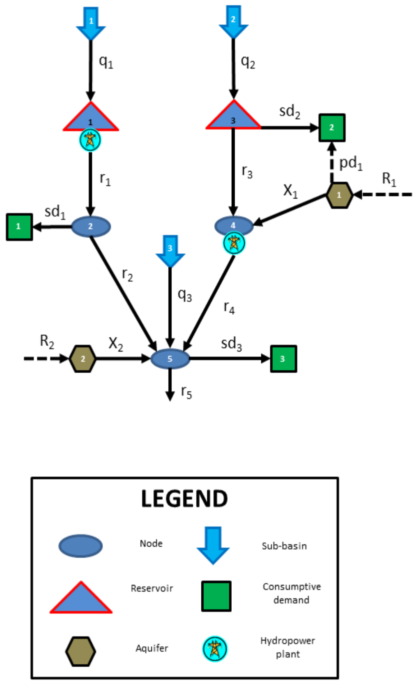
The system operation problem is subject to the surface water mass balance conservation equation (Eq. 3.3) for every time period *t*.

$$s_{t+1} = s_t \; - l_t \; + C^q \cdot q_t \; + C^n \cdot r_t \; + C^X \cdot X_t \; - C^d \cdot sd_t \qquad \textbf{3.3}$$

Where s_{t+1} vector of storages at the beginning of time stage *t+1*, s_t vector of storages at the beginning of time stage *t*; l_t vector of losses (including evaporation and seepage); C^q inflow connectivity matrix; q_t vector of inflows from hydrological sub-basins; C^n node connectivity matrix; r_t vector of releases from nodes; C^X stream-aquifer interaction connectivity matrix; X_t vector of exchanged flows between surface and ground waters due to stream-aquifer interaction (positive if there is a groundwater discharge); C^d demand connectivity matrix; and sd_t vector of surface water deliveries to consumptive demands. The operation problem is also subject to the groundwater mass balance conservation (Eq. 3.4).

$$G_{t+1} = G_t + R_t - (C^X)^T \cdot X_t - C^p \cdot pd_t \qquad \textbf{3.4}$$

Where G_{t+1} vector of aquifer storages at the beginning of time stage *t+1*, G_t vector of aquifer storages at the beginning of time stage *t*; R_t vector of aquifer recharge; C^p pump connectivity matrix; and pd_t vector of pumping rates from the aquifer to consumptive demands. An example of a multireservoir system including aquifers and the corresponding connectivity matrices is shown in Fig. 3.1. The stream-aquifer interaction term is obtained using the equations of the Embedded Multireservoir Model, able to model complex relationships between surface and groundwater bodies (presented in detail in section 3.3).



$$C^n = \begin{pmatrix} -1 & 0 & 0 & 0 & 0 \\ +1 & -1 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & +1 & -1 & 0 \\ 0 & +1 & 0 & +1 & -1 \end{pmatrix}$$

$$C^q = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \qquad C^X = \begin{pmatrix} 0 & 0 \\ 0 & 0 \\ 0 & 0 \\ 1 & 0 \\ 0 & 1 \end{pmatrix}$$

$$C^d = \begin{pmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 1 \end{pmatrix} \qquad C^p = \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

Fig. 3.1: Example of a multireservoir system and the associated connectivity matrices

The interactions between surface and ground waters considered by the algorithm are three: 1) aquifer recharge *R*; 2) aquifer pumping from consumptive demands *pd*; and 3) water exchanged between river reaches and groundwater bodies through stream-aquifer interaction *X*. The optimization problem described can be applied to any water resource system configuration within the applicability limits of the SDDP algorithm, which can handle very large water resource systems (e.g. Pereira and Pinto, 1985; Tilmant et al., 2010; Tilmant and Kelman, 2007); and within the range of application of the EMM, which can reproduce complex stream-aquifer interactions (Andreu and Sahuquillo, 1987; Estrela and Sahuquillo, 1997; Pulido-Velazquez et al., 2008, 2006a, 2005; Sahuquillo, 1983).

3.2.1. *Immediate benefits*

The immediate benefits B_t have been divided into two components (Eq. 3.5).

$$B_t(s_t, r_t, q_t) = \sum_{d} BC_t^d + \sum_{hpp} BH_t^{hpp} \qquad \textbf{3.5}$$

Where BC_t^d benefits associated with consumptive uses; *d* consumptive demand; BH_t^{hpp} benefits associated with hydropower; *hpp* hydropower plant. If desired, economic penalties can also be included to undesired situations like non-turbined releases and minimum flow and storage violations.

Consumptive uses

These benefits can be obtained as the integration of the demand function or curve between zero and the level of supply, minus the pumping costs if groundwater resources are used (Eq. 3.6).

$$BC_t^d = \int_{x=0}^{x=sd_t^d} DC_t^d(x)dx - \sum_{aq} PC_t^{d,aq} \qquad \textbf{3.6}$$

Where DC_t^d demand curve for time stage *t*; sd_t^d current total net supply level (surface and/or groundwater) from the system operation; and $PC_t^{d,aq}$ pumping costs, calculated as:

$$PC_t^{d,aq} = UPC_t^{d,aq} \cdot pd_t^{d,aq} \qquad \textbf{3.7}$$

Where *d* demand that pumps, *aq* aquifer from which it pumps; $UPC_t^{d,aq}$ unitary pumping cost and $pd_t^{d,aq}$ amount of groundwater pumped. The unitary pumping cost can be considered as fixed or variable depending on the aquifer storage.

Hydropower benefits

The hydropower production formulation is shown in Eq. 3.8.

$$HP_t^{hpp} = \frac{h_t^{hpp} + h_{t+1}^{hpp}}{2} \cdot qr_t^{hpp} \cdot \eta_{hpp} \qquad \textbf{3.8}$$

Where HP_t^{hpp} hydropower production obtained in time stage t at power plant *hpp*; h_t^{hpp} and h_{t+1}^{hpp} heads in power plant *hpp* at time stages *t* and *t+1*, which can be the heads in the associated reservoir (impoundment), or the net jump of the power plant (run-of-river); qr_t^{hpp} turbined flow during time stage *t* (equal to the release from the associated system node subject to the plant capacity and the existence on minimum flow rates); and η_{hpp} generation efficiency, which equals the global dimensionless efficiency coefficient times a conversion factor that depends on the units (if time in month, elevation in m, flow in Mm^3 and energy in GWh, it equals 0.0027222). Once the production is obtained, the benefits are calculated as production times the energy price or the value of energy in non-market situations.

Hydropower production is a potential source of nonconvexities that may hinder the applicability of SDDP, which requires the benefit-to-go functions to be convex (Tilmant et al., 2008; Tilmant and Kelman, 2007). A way to assure that these nonconvexities do not affect the benefit-to-go function representation is to assume that the hydropower production is dominated by the turbined release rather than the head (Tilmant and Kelman, 2007). This assumption is valid if changes in head are small compared with the total head (Tilmant et al., 2008).

3.2.2. Benefit-to-go function representation

Any SDDP formulation estimates the F_{t+1} function using a set of hyperplanes (piecewise linear approximations) obtained by sampling and extrapolation through a Benders decomposition scheme (Goor, 2010; Pereira and Pinto, 1985). Each hyperplane is built as follows: a sample point is chosen and a linear approximation of the F_{t+1} function is calculated using its value and its derivatives at this point (Fig. 3.2). The F_{t+1} function must be linear or at least convex, fulfilling the Kuhn-Tucker conditions for optimality (Goor, 2010), in order to ensure that the piecewise linear segments are always offering an upper bound of the true benefit function.

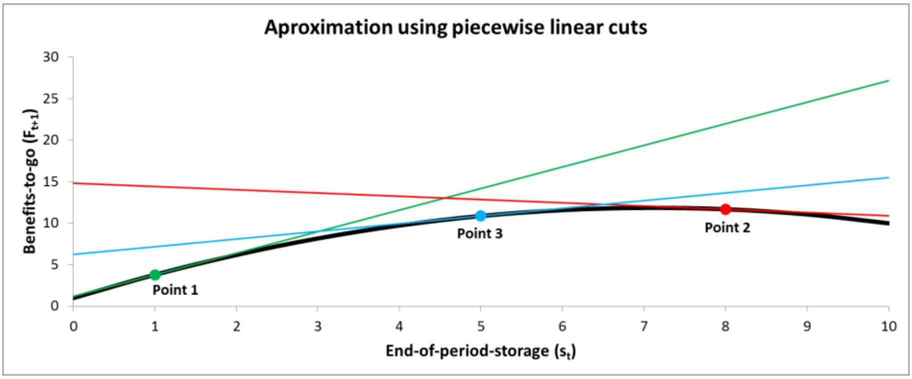


Fig. 3.2: Function approximation using piecewise linear cuts

In the one-stage subproblem (Eq. 3.2), F_{t+1} is represented as one scalar bound to a set of constraints (added to the optimization problem) corresponding to the hyperplanes equations:

$$\begin{cases} F_{t+1} \leq \varphi_{t+1}^{1} \cdot s_{t+1} + \omega_{t+1}^{1} \cdot G_{t+1}^{aqr} + \gamma^{1}{}_{t+1} \cdot q_t + \beta_{t+1}^{1} \\ \vdots \\ \vdots \\ F_{t+1} \leq \varphi_{t+1}^{l} \cdot s_{t+1} + \omega_{t+1}^{l} \cdot G_{t+1}^{aqr} + \gamma_{t+1}^{l} \cdot q_t + \beta_{t+1}^{l} \\ \vdots \\ \vdots \\ F_{t+1} \leq \varphi_{t+1}^{L} \cdot s_{t+1} + \omega_{t+1}^{L} \cdot G_{t+1}^{aqr} + \gamma_{t+1}^{L} \cdot q_t + \beta_{t+1}^{L} \end{cases} \quad \textbf{3.9}$$

Where *l* linear approximation of the benefit-to-go function; s_{t+1} vector of start-of-period storages in *t+1*; G_{t+1}^{aqr} vector of start-of-period groundwater storages in *t+1*; q_t vector of previous inflows to time step *t+1*; φ^l vector of slopes with respect to the storage term; ω^l vector of slopes with respect to the groundwater term (one term per aquifer cell); γ^l vector of slopes with respect to the previous inflow term; and β^l vector of independent terms.

3.2.3. Constraints

In addition to the constraints introduced by the water mass balance conservation (Eq. 3.3 and 3.4), and by the representation of F_{t+1} (Eq. 3.9), the one-stage subproblem is subject to the limits on storages (capacity and dead storage), streamflows (minimum environmental flow and stream capacity) and consumptive uses; as well as water losses (evaporation and seepage in reservoirs and seepage in streams) and hydropower capacity.

3.2.4. Stochastic modeling procedures

The inflow uncertainty is represented in the SDDP algorithm by an analytical stochastic multivariate autoregressive model (AR), as the ones described in Hipel and McLeod (1994); and Salas et al. (1980). Although AR models of order 2 and higher can be employed in the SDDP method (Maceira and Damázio, 2004; Pina et al., 2016), the classical formulation of the SDDP, with an AR model of order 1, has been adopted in this thesis. This efficient representation avoids the need of discretization schemes that hinder the use of the standard SDP in large water resource systems. Assuming a vector of previous standard inflows (null mean and unit standard deviation) $\{z_{t-1}\}$ obtained after $\{q_{t-1}\}$, the AR(1) model estimates the standard vector of current inflows $\{z_t\}$ as:

$$z_t = \delta_{1,t} \cdot z_{t-1} + \omega_{0,t} \cdot \varepsilon_t \quad \text{3.10}$$

Where $\delta_{1,t}$ statistical relationship between the previous inflows vector and the current one; $\omega_{0,t}$ residuals' coefficients; and ε_t randomly-distributed residuals that follow a standard normal distribution (white noise). If δ and ω_0 do not depend on t the model is named to be an AR(1) model with constant parameters; otherwise it is named as an AR(1) model with periodic parameters (Salas et al., 1980).

The SDDP algorithm usually assumes normally-distributed inflows. However, there are situations in which non-normally inflows must be assumed. In these, the SDDP algorithm can be used by building two autoregressive models:

1. One autoregressive model whose features must agree with the inflow characteristics, assuming non-normally inflows if necessary, to generate inflow time series and openings. Alternative approaches to generate inflow openings and time series can be used if found adequate.
2. One AR(1) model assuming normally-distributed inflows, whose $\delta_{1,t+1}$ coefficients are going to be used in the calculation of the hyperplanes' parameters. This model should not be used to generate openings and/or time series unless its adequacy has been properly tested.

3.3. MODELING STREAM-AQUIFER INTERACTION

The distinct feature of the CSG-SDDP, the inclusion of stream-aquifer interactions, is made using the conceptual Embedded Multireservoir Model (EMM, Pulido-Velazquez et al. 2005). Its formulation is based on the structure of the analytical solution of the stream-aquifer interaction problem obtained from the groundwater flow equation applied to linear systems (confined aquifers or unconfined aquifers with negligible head variations compared to its thickness), as well as its analogy with the state equation of the groundwater linear reservoir model (Sahuquillo, 1983). This conceptual model represents each stream-aquifer interaction modeled as the summation of the drainage of one or more reservoirs with discharges linearly proportional to the volume stored above the outlet (Fig. 3.3).

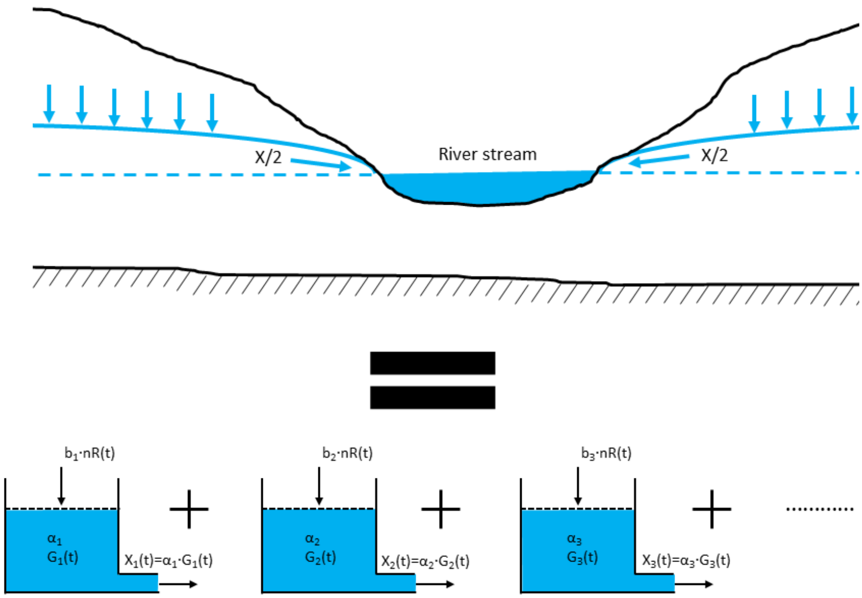


Fig. 3.3: Conceptualization of the embedded multireservoir model
Source: adapted from Pulido-Velazquez et al. (2005)

Although the EMM is unable to obtain spatially-distributed heads and internal groundwater flows, so it cannot be considered as an aquifer model, it can provide accurate representations of stream-aquifer interactions while maintaining the balance of groundwater resource availability, even in karstic aquifers (Estrela and Sahuquillo, 1997). Due to its capability to adequately reproduce stream-aquifer interactions, the EMM is used in some general

Decision Support System shells, in which a wide range of system configurations can be modeled (Andreu et al., 1996). Due to this, combine EMM with SDDP is a promising alternative, since the focus of the resulting algorithm is kept on the reservoir management rather than on groundwater. Further information on analytical and numerical derivations of the EMM and its relation with the eigenvalue method (Sahuquillo, 1983) can be found in Pulido-Velazquez et al. (2008, 2006a, 2005).

Each external action or stress applied to the aquifer is divided among a set of linear reservoirs with different discharge coefficients α^{aqr} according to stress allocation factors b^{aqr}. For each *aqr* reservoir, the linear problem is solved as:

$$G_{t+1}^{aqr} = G_t^{aqr} \cdot e^{-\alpha^{aqr}\Delta t} + \frac{b^{aqr} \cdot nR_t}{\alpha^{aqr}}(1 - e^{\alpha^{aqr}\Delta t}) \quad \textbf{3.11}$$

$$X_t^{aqr} = G_t^{aqr} - G_{t+1}^{aqr} + b^{aqr} \cdot nR_t \quad \textbf{3.12}$$

$$\sum_{aqr} b^{aqr} = 1 \quad \textbf{3.13}$$

Where G_t^{aqr} groundwater stored at the start of time stage *t* in the linear reservoir *aqr*, *Δt* time increment, nR_t net recharge (recharge minus pumping), and X_t^{aqr} groundwater discharge (outflow) from linear reservoir *aqr*. When G_t^{aqr} becomes negative (storage level below the outlet), X_t^{aqr} turns into negative too, representing an inflow to the aquifer from the river (losing river). Eq. 3.11 calculates the storage at each linear reservoir for the end of time stage *t* (beginning of *t+1*) and Eq. 3.12 obtains the discharge by water balance. Once they are solved for all the linear reservoirs that conceptualize the aquifer, the total aquifer storage G_t and the total outflow X_t is the summation over the *aqr* terms. The EMM assumes no internal connections between linear reservoirs, so equations 3.11 to 3.13 are applied separately to each one.

The net groundwater discharge nR_t is calculated as the sum of all the recharge flows (excluding stream-aquifer interaction) minus the abstractions. If a linear aquifer response is assumed (valid for confined aquifers or unconfined aquifers with negligible head variations compared with its thickness), the principle of superposition can be applied, and the behavior associated with the whole set of actions can be obtained as the summation of the effects caused by each individual action (pumping, rainfall, percolation, artificial recharge, etc.) applied to the aquifer (Pulido-Velazquez et al., 2005).

If this principle can be applied, it is not necessary to reproduce the response of the aquifer to the natural stresses, since the natural stream-aquifer interaction is already included in the natural regime inflow time series. The calculation of the aquifer response due to natural stresses is cumbersome, since it requires a large amount of hydrological and aquifer hydraulic properties for the desired analysis period. If the conditions for a linear response cannot be fulfilled, assuming a linear behavior can lead to significant errors in the stream-aquifer interaction assessment.

3.4. CSG-SDDP STAGES

In the SDDP algorithm, the F_{t+1} function is built using an iterative process with a backward optimization and a forward simulation (Fig. 3.4). In the backward step, the hyperplanes that bind F_{t+1} are estimated. In the forward one, the F_{t+1} representation built is used to optimize the system. At the end of each iteration, the accuracy of F_{t+1} is evaluated and, if insufficient, it is improved adding more sample points and piecewise linear approximations (also known as cuts). The process is repeated until enough accuracy is found.

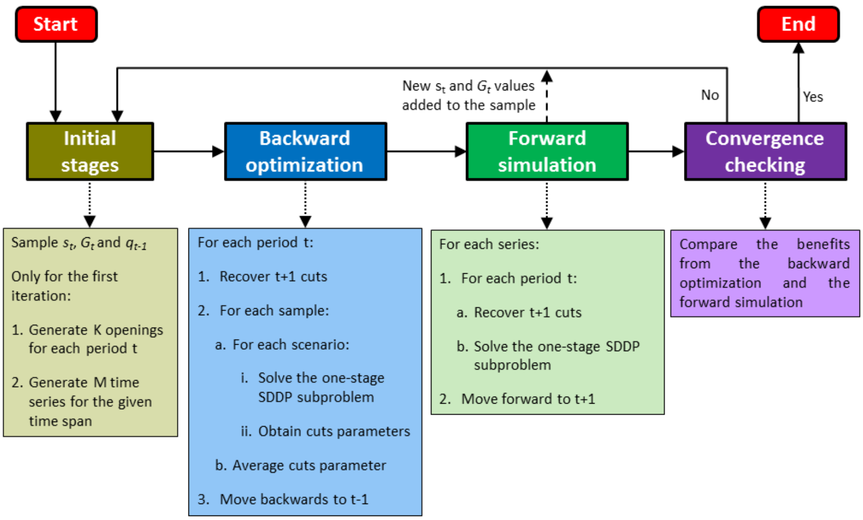


Fig. 3.4: SDDP general flowchart

3.4.1. Initial stages

Sample initialization

Each time stage t needs a vector of sampled start-of-period storages $\{s_t^o\}$, a vector of sampled previous inflows $\{q_{t-1}^o\}$ and a vector of sampled start-of-period groundwater levels $\{G_t^o\}$. The inflow samples can be obtained using the historical records of the analysis period, or the results of a hydrological or autoregressive model. The reservoir and groundwater storage samples for the first iteration can be estimated, as done by Pereira and Pinto (1985), by using a previous *greedy* or *blind* forward-moving optimization, in which the one-stage subproblem is solved without considering future benefits.

Stochastic modeling

The previously-defined AR model, or any suitable alternative employed for inflow generation, is used to obtain the required inflow scenarios:

- Generate, for all the *T* time stages of the planning horizon, *K* inflow openings $\{q_t\}^k$ conditioned by the sampled inflows $\{q_{t-1}^o\}$
- Generate *M* inflow scenarios $(\{q_1\}, \dots, \{q_t\}, \dots, \{q_T\})^m$ conditioned by the inflows sampled at t=1 $\{q_0^o\}$

3.4.2. Backward optimization

In the backward optimization the F_{t+1} function is estimated, for each time stage of the analysis period, solving the one-stage subproblem for *L* samples and *K* inflow openings per sample (Goor, 2010; Tilmant and Kelman, 2007). The number of subproblems solved per iteration is *T·L·K*. The pseudo-code corresponding to the backward optimization, as stated in Goor (2010), is:

```
Establish the number L of cuts to be used in the current iteration
Initialize the end-of-horizon cut values φ^l_{T+1}, γ^l_{T+1}, ω^l_{T+1} and β^l_{T+1}
FOR   t=T to t=1
      Retrieve the cut parameters calculated at the stage t+1: φ^l_{t+1}, γ^l_{t+1}, ω^l_{t+1} and β^l_{t+1}
      FOR   l=1 to L
            FOR   k=1 to K
                  Solve the one-stage SDDP subproblem
                  Calculate cut parameters φ^{l,k}_t, γ^{l,k}_t, ω^{l,k}_t
            END
```

Take the expectation over the openings to obtain φ_t^l, γ_t^l and ω_t^l
Calculate β_t^l
Store the total benefit values F_t^l

END

END

The parameters φ_t^l, γ_t^l, ω_t^l and β_t^l correspond to the vector of slopes with respect to the storage, the vector of slopes with respect to the previous inflows, the vector of slopes with respect to the aquifer storages, and the vector of independent terms. As stated in Goor (2010); Pereira and Pinto (1985); and Tilmant and Kelman (2007), their estimation can be done regarding to the primal and dual information available after solving the one-stage subproblem for each sample and opening.

At stage *t+1*, after the solution of the one-stage SDDP subproblem, the slope with respect to the storages $\varphi_{t+1}^{l,k}$ can be obtained as:

$$\varphi_{t+1}^{l,k} = \frac{\partial F_{t+1}^{l,k}}{\partial s_{t+1}} = \lambda_{t+1}^{l,k,ne} \tag{3.14}$$

Where $\lambda_{t+1}^{l,k,ne}$ vector of dual variables associated with the mass balance equations (Eq. 3.3) of the *ne* nodes that are reservoirs. The φ_{t+1}^l parameter can be obtained by taking the expectation over all the openings:

$$\varphi_{t+1}^l = \frac{1}{K} \cdot \sum_{k=1}^{K} \varphi_{t+1}^{l,k} \tag{3.15}$$

The slope with respect to the inflows $\gamma_{t+1}^{l,k}$ can be estimated as:

$$\begin{aligned} \gamma_{t+1}^{l,k} &= \frac{\partial F_{t+1}^{l,k}}{\partial q_t} = \frac{\partial F_{t+1}^{l,k}}{\partial q_{t+1}} \cdot \frac{\partial q_{t+1}}{\partial q_t} \\ &= \left(\lambda_{t+1}^{l,k,nq} + \sum_{cut=1}^{L} \lambda_{t+1}^{l,k,cut} \cdot \gamma_{1,t+2}^{cut} \right) \cdot \left(\delta_{1,t+1} \cdot \frac{\sigma_{t+1}}{\sigma_t} \right) \end{aligned} \tag{3.16}$$

Where *cut* piecewise linear approximation of the F_{t+2} function (same meaning as *l* but referred to the *t+2* stage); $\lambda_{t+1}^{l,k,nq}$ vector of dual variables associated with the mass balance equations of the *nq* nodes that are receiving inflows (Eq. 3.3); $\lambda_{t+1}^{l,k,cut}$ dual variable associated with the constraint that represents the *cut* piecewise linear approximation of F_{t+2}

(Eq. 3.9); $\gamma_{1,t+2}^{cut}$ vector of slopes with respect to the immediate previous inflows of the *cut* piecewise linear approximation of F_{t+2}; $\delta_{1,t+1}$ matrix obtained from the autoregressive model calculated assuming normally-distributed inflows; σ_{t+1} standard deviation of the inflows in stage *t+1*. The γ_{t+1}^{l} can be calculated as the expectation over all the openings:

$$\gamma_{t+1}^{l} = \frac{1}{K} \cdot \sum_{k=1}^{K} \gamma_{t+1}^{l,k} \qquad \textbf{3.17}$$

The slope with respect to the groundwater levels $\omega_{t+1}^{l,k}$ can be calculated in CSG-SDDP as:

$$\omega_{t+1}^{l,k} = \frac{\partial F_{t+1}^{l,k}}{\partial G_{t+1}} = \lambda_{t+1}^{l,k,aqr} \cdot e^{-\alpha^{aqr}} + \lambda_{t+1}^{l,k,X} \qquad \textbf{3.18}$$

Where $\lambda_{t+1}^{l,k,aqr}$ vector of dual variables associated with the calculation of the end-of-period groundwater storages (Eq. 3.11); $\lambda_{t+1}^{l,k,X}$ vector of dual variables associated with the mass balance equation used to compute the groundwater discharge (Eq. 3.12). The ω_{t+1}^{l} parameter can be obtained by taking the expectation over all the openings:

$$\omega_{t+1}^{l} = \frac{1}{K} \cdot \sum_{k=1}^{K} \omega_{t+1}^{l,k} \qquad \textbf{3.19}$$

Once φ_{t+1}^{l}, γ_{t+1}^{l}, and ω_{t+1}^{l} are obtained, the independent term β_{t+1}^{l} can be calculated as:

$$\beta_{t+1}^{l} = \frac{1}{K} \cdot \sum_{k=1}^{K} F_{t+1}^{l,k} - \varphi_{t+1}^{l} \cdot {s^{o}}_{t+1}^{l} - \gamma_{t+1}^{l} \cdot {q^{o}}_{t}^{l} - \omega_{t+1}^{l} \cdot {gw^{o}}_{t}^{l} \qquad \textbf{3.20}$$

Given that the piecewise linear approximations of F_{t+1} offer an upper bound of its true value, the total benefits obtained each time stage of the backward recursion (F_t) are overestimated. Once the last stage of the backward recursion (*t=1*) is reached, the upper bound $\overline{\mathrm{Z}}$ (overestimation) of the true benefits obtained can be defined as the value of F_1 associated with the sampled storage and inflow variables in *t=1* (Eq. 3.21).

$$\overline{Z} = F_1\left({s^{o}}_{1}, q_0^{o}\right) \qquad \textbf{3.21}$$

3.4.3. Forward simulation

The estimations of F_{t+1} from the backward optimization are employed in a forward-moving loop in which the one-stage subproblem is solved for the M inflow scenarios previously generated. For each scenario, the total benefits obtained $\underline{\mathrm{Z}}^{\mathrm{m}}$ are a lower bound of the true benefits, given that the F_{t+1} functions are overestimated and, consequently, the model favors future benefits instead of the current ones. The pseudo-code corresponding to the forward simulation stage, as stated in Goor (2010), is:

```
FOR  m=1 to m=M
     FOR     t=1 to T
             Retrieve cut parameters for stage t+1: φ_t^l, γ_t^l, ω_t^l and φ_t^l, γ_t^l, ω_t^l calculated
             in the backward optimization
             Solve the one-stage SDDP subproblem
             Store the immediate benefits obtained B_t^m
     END
     Obtain the lower bound associated with the m scenario: Z^m
END
```

The lower bound for each inflow scenario can be obtained as:

$$\underline{Z}^m = \sum_{t=1}^{T} B_t^m \tag{3.22}$$

The expected lower bound can be estimated as:

$$\underline{Z} = \frac{1}{M}\sum_{m=1}^{M} \underline{Z}^m \tag{3.23}$$

The standard deviation associated with the expected lower bound is:

$$\sigma_{\underline{Z}} = \sqrt{\frac{1}{M-1}\cdot\sum_{m=1}^{M}\left(\underline{Z}^m - \underline{Z}\right)^2} \tag{3.24}$$

Using the expected lower bound and the standard deviation, a 95% confidence interval can be built around the expectation:

$$\left[\underline{Z} - 1.96\cdot\frac{\sigma_{\underline{Z}}}{\sqrt{M}}, \underline{Z} + 1.96\cdot\frac{\sigma_{\underline{Z}}}{\sqrt{M}}\right] \tag{3.25}$$

3.4.4. *Convergence checking*

If the upper bound $\overline{\mathrm{Z}}$ is inside the confidence interval defined around the lower one, then the approximation of the F_{t+1} function is acceptable and the problem is solved. Otherwise, a new iteration is needed: a new set of sampled values $\{s_t^o\}$, $\{G_t^o\}$ and $\{q_{t-1}^o\}$ is added to the previous ones and the procedure is started again with more hyperplanes representing F_{t+1}. The natural candidates to the new $\{s_t^o\}$ and $\{G_t^o\}$ sample are the values obtained in the last forward simulation stage. As the number of samples increases with the iteration number, each new one requires more one-stage subproblems to be solved in the backward optimization stage.

3.4.5. *Steady-state optimization*

The main results of the previous methodology are the piecewise linear approximations of F_{t+1} for each time stage of the planning horizon. To obtain *steady* F_{t+1} approximations able to be used in further runs, a characteristic year could be chosen from the analysis period, using its F_{t+1} approximations in further optimization operations (Rougé and Tilmant, 2016). To choose the characteristic year, two requirements must be fulfilled.

1. Its hydrological characteristics must not depart from the general pattern observed in the historical data series period
2. It must be located far enough from the bounds of the analysis period to avoid perturbations caused by either the initial or the final boundary conditions

Once it is chosen, future optimization procedures would consist in solving forward the one-stage subproblem using the F_{t+1} piecewise linear segments corresponding to this year. In this way, a steady decision-making process can be reproduced and tested under different conditions.

3.5. ESPAT TOOL

A general-purpose DSS shell tool, named *Explicit Stochastic Programming Advanced Tool* (ESPAT), has been created for the implementation of the CSG-SDDP and alternative optimization approaches. It eases the setup and run of stochastic programming models by providing a uniform framework that can be applied regardless of the water resource system configuration, avoiding the need of *ad hoc* codes. The systems to which it could be applied are the ones within the applicability limits of the CSG-SDDP algorithm (section 3.2).

The main parts of the ESPAT tool are the user interface and the codes. The latter have been programmed using the GAMS language (General Algebraic Modeling System, Brooke et al. 1998). The interface guides the user in the introduction of the desired model features (surface hydrology, hydraulic infrastructure, economic features, stream-aquifer interaction, seepage losses and so on). The codes are executed from the interface, so no knowledge about GAMS is required to run ESPAT, being the following:

- ESPAT_R: solves the SDDP algorithm as presented in Goor (2010); Pereira and Pinto (1985, 1991); and Tilmant and Kelman (2007).
- ESPAT_RA: solves the CSG-SDDP algorithm as presented before.
- ESPAT_DET: performs a deterministic optimization with the same features as the ESPAT_RA module.
- ESPAT_SDP: solves the SDP algorithm without considering stream-aquifer interactions.

3.5.1. ESPAT user interface

General features

The user interface employed by the ESPAT tool consists of an MS Excel workbook, supported by several macros that communicate it with the codes and control their execution. The data are introduced using different Excel sheets. The interface plots the progress of the run execution and, if no execution errors are found, generates output Excel files according to the module executed. All the algorithms share the same interface, so it is easy to move from one approach to another. In addition, having the same input mechanism ensures that the same system configuration and mathematical descriptions of the physical and economic processes and features are used by all the algorithms.

Required inputs

1. General features of the problem: type of solving procedures, module parts to be executed, convergence limits, number of iterations, number of inflow scenarios or openings, etc.

MODEL GENERAL FEATURES FOR ESPAT_DET, ESPAT_R AND ESPAT_RA

Type of ESPAT_DET initial point obtention	ESPAT as base
Type of SDDP scenario solving procedure	GUSS on all
SDDP codes program execution	Whole program
Stochastic modeling procedure desired	AR-model-based
Origin of the first storage sample values in SDDP	Blind simulation
Convergence limit in percentaje (only if series=1)	
Confidence interval coefficient (only if series>1)	0.05
Maximum number of iterations	15
Number of starting cuts, or cut number in only reoptimization	1
Number of lag periods of the autoregresive model	1
Number of openings calculated for each sample	20
Number of forward simulation series	20
Starting year of the historical series subsample	38
Number of years of the historical series subsample	5
Number of year to use as steady cut value provider	2
Penalty on minimum flow violation	1.5
Penalty on minimum storage violation	1

MODEL GENERAL FEATURES FOR ESPAT_SDP

Type of problem	Maximization
Recursion primary convergence limit (Benefits)	0.01
Recursion maximum number of iterations	20
Optimization module previously executed?	Yes
Recursion module previously executed?	Yes
Reoptimization desired?	Yes
Optimization module quick mode	Enabled
Reoptimization interpolation mechanism	Piecewise linear
Reoptimization module reservoir prevalence mode	Enabled
Type of reoptimization desired	Deterministic

Fig. 3.5: Model features input table for SDDP and SDP procedures in the ESPAT tool

2. General features of the system: time horizon, time step, nodes, reservoirs, aquifers, hydropower plants, sub-basins, demands, etc.
3. Connectivity matrices: nodes, wells, reservoirs, sub-basins, intakes.
4. Reservoir features: minimum and maximum storages, initial state, head and surface curves, infiltration curves, aquifer which receives the infiltrated flows, evaporation rates, discrete values, etc.

SYSTEM FEATURES

Number of temporal stages per year (t)	12
Number of years of the historical period (hist_year)	69
Number of nodes in the system (nod)	11
Number of reservoirs in the system (e)	2
Number of aquifers in the system (aq)	2
Numer of hydropower plants (hpp)	1
Number of hydrological sub-basins (p)	2
Number of demands (d)	4
Coefficients of demand benefit curves (gd)	4

Fig. 3.6: System features input table of the ESPAT tool

5. Demand features: demand values, return flows, pumped aquifer, demand benefits, pumping costs, etc.
6. Stream features: maximum and minimum flows, infiltration rates, aquifer which receives infiltration, connected aquifer, etc.
7. Hydropower plant features: associated reservoir (if there is one), turbine capacity, efficiency, elevation, benefits, etc.
8. Aquifer features: number of linear reservoirs, initial state, discharge coefficients, distribution coefficients for all the actions, etc.
9. Stochastic prediction scheme features: inflow means, inflow standard deviations, autoregressive model lag matrix, openings, time series, scenario weights, historical records, Markov chain, etc.

3.5.2. *ESPAT_R*

ESPAT_R solves the SDDP method as presented in Goor (2010); Pereira and Pinto (1985, 1991); and Tilmant and Kelman (2007); neither considering aquifers nor stream-aquifer interactions. It does not implement any autoregressive modeling procedure, whose results (correlation matrices, openings and series) must be introduced as inputs. Additionally, the code requires the initial sampled values for storages.

The ESPAT_R code is divided into two modules: the SDDP module and the steady-state module. In the first one the SDDP stages are executed. In the second one a characteristic year is chosen and the system is optimized moving forward using the benefit-to-go functions of this year. The code allows the user to execute one of them or both, although the steady-state needs a set of F_{t+1} functions of the characteristic year as input (Fig. 3.7).

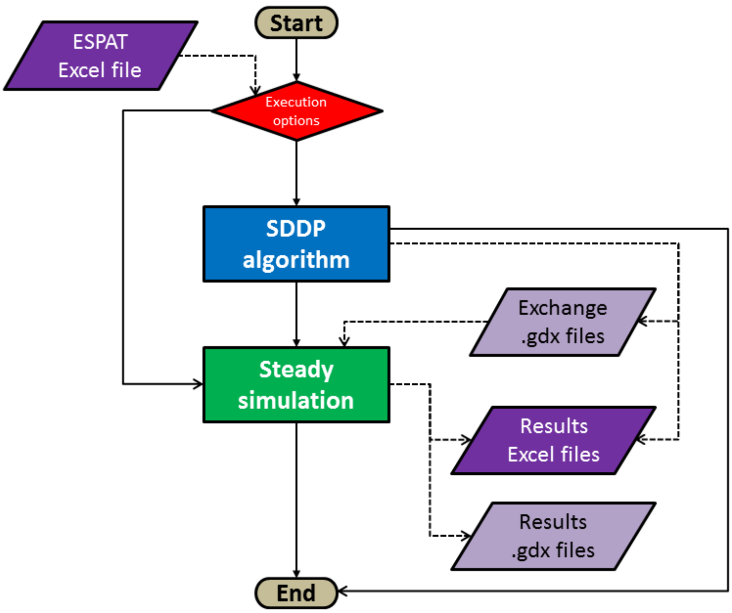


Fig. 3.7: ESPAT_R code general flowchart

The results offered by this code are the state variables at the reservoir nodes (storage, evaporation and seepage losses), streamflows, outflows of the system, seepage losses and environmental flows, demand deliveries, deficits and demand benefits, turbined flows, energy production and energy benefits, and the water values (dual variables) at all the system's nodes.

3.5.3. ESPAT_RA

ESPAT_RA solves the CSG-SDDP method as presented in this PhD thesis, including stream-aquifer interactions. It possesses the same features, modular division and flowchart as ESPAT_R.

3.5.4. ESPAT_SDP

ESPAT_SDP implements the standard SDP algorithm (Nandalal and Bogardi, 2007; Stedinger et al., 1984). Originally it was a separate program named SDP_GAMS (Macian-Sorribes and Pulido-Velazquez, 2014).

This code is subject to the curse of dimensionality. It neither includes stream-aquifer interaction nor hydropower. After calculating the optimal operation, the code interpolates the benefit-to-go functions to use them in a forward-moving simulation, as done in Tejada-Guibert et al. (1993). It possesses a modular approach in order to optimize its execution (Fig. 3.8.).

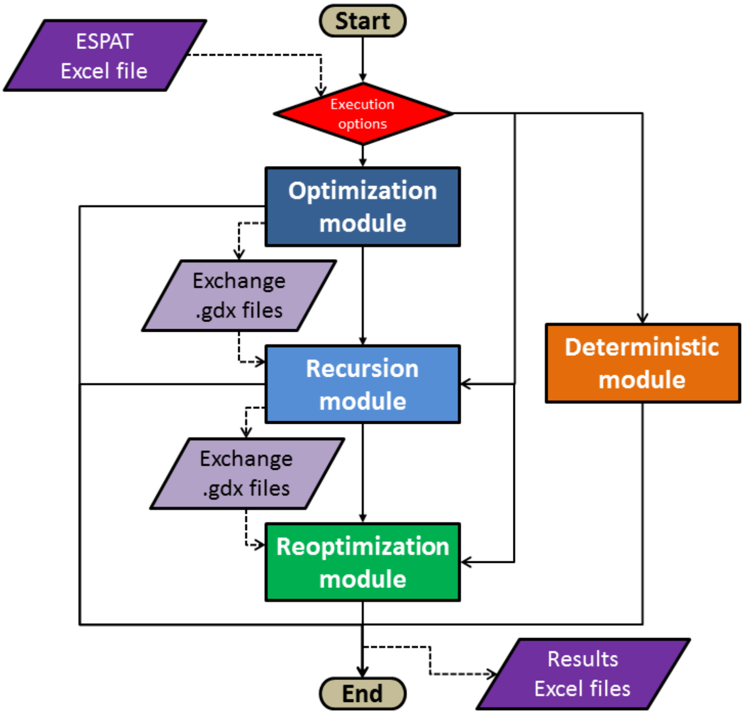


Fig. 3.8: ESPAT_SDP code general flowchart

Its results are the state variables at the reservoir nodes (storage, evaporation and seepage losses), the way water moves between nodes (flows, outflows of the system and seepage losses), the consumptive demands (deliveries, deficits and benefits), and the water values (dual variables) at the system's nodes.

3.5.5. ESPAT_DET

ESPAT_DET performs deterministic optimizations with perfect foresight of future inflows. The elements considered and the range of water resource systems that can be analyzed are the same as ESPAT_RA. It allows an immediate transition between a stochastic steady-state simulation and a deterministic optimization. The results obtained are the same as ESPAT_RA.

Mathematically, it implements a non-linear deterministic programming scheme, requiring a suitable initial point, which can be defined using four different ways (Fig. 3.9):

a) Default initial point provided by GAMS (null value or the lower bound).
b) Piece-by-piece approach, as described in Cai et al. (2001), with the following addition scheme:
   i. Performing a blind simulation over the system without hydropower and stream-aquifer interaction.
   ii. Solving the system without hydropower and stream-aquifer interaction using as initial point the blind simulation results.
   iii. Solving the system without stream-aquifer interactions employing as initial point the previous problem solution.
   iv. Solving the system with stream-aquifer interactions but without pumping using as initial point the previous problem solution.
   v. Solving the system with its full configuration using as initial point the previous problem solution.
c) Use the results of a simulation code (STIG, explained in section 4.2).
d) Use the results of a steady-state stochastic optimization procedure from ESPAT_R or ESPAT_RA.

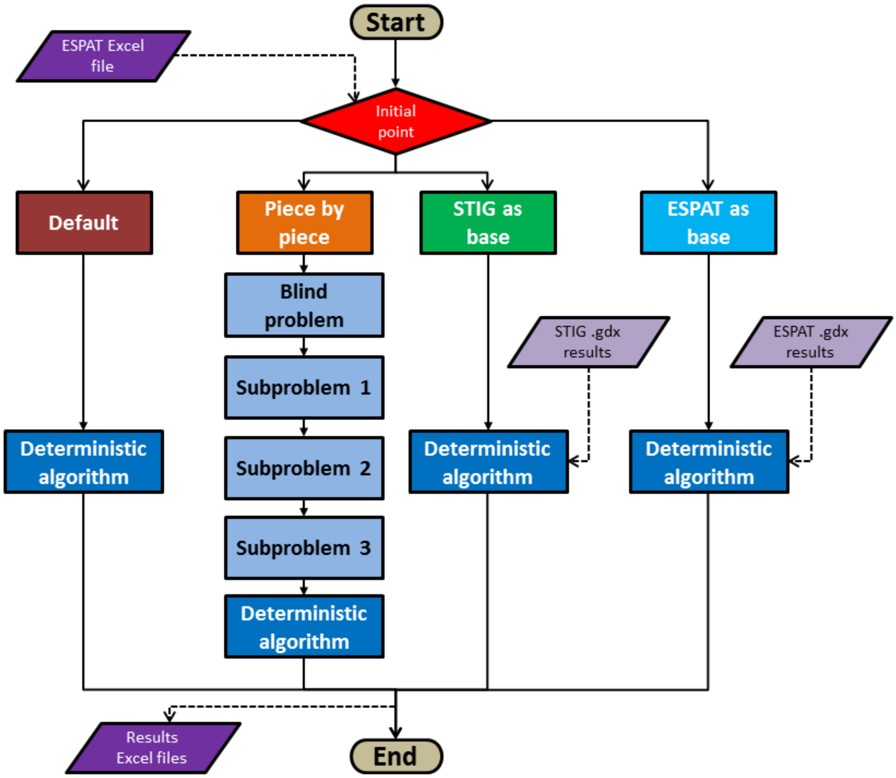


Fig. 3.9: ESPAT_DET code general flowchart

4. METHODS 2: DSS FOR THE SEASONAL OPERATION OF A MULTIRESERVOIR SYSTEM BASED ON EXPERT KNOWLEDGE[2]

To ensure a close reproduction of the real decision-making of the system operation, a continuous interaction between experts (system operators) and modelers is required. The ability of fuzzy logic to acquire expert judgment and to combine it with numerical data (see subsection 2.2.3) make it a suitable option to merge expert knowledge with optimization results. To do so, decision-making processes and mathematical models need to be assessed and built in a fully collaborative process, in which experts should be involved from the very beginning (Loucks and van Beek, 2005).

In the approach presented, expert knowledge from system operators is used to determine the decision-making processes currently carried out for the seasonal operation of a given water resource system, including the inflow forecasting mechanisms (if any) and the operating rules. Fuzzy rule-based (FRB) systems are used to mathematically reproduce them. The FRB systems are quantified using expert knowledge (through the methods presented in subsection 2.2.3) and, if required, historical records (which are the product of the historical decisions).

Once the current decision-making processes and operating rules are mathematically reproduced, they are improved using the results from an optimization algorithm. Therefore, the resulting mathematical representation is able to identify what should be changed in the seasonal operation while respecting as much as possible the current practices. This approach is especially suited to water resource systems in which the decision-making stages are set by law or tradition. It is also applicable in systems with a large number of stakeholders, in which agree on improving

[2] The methodology presented in this Chapter is based on Macian-Sorribes and Pulido-Velazquez (2017). Its use in this thesis complies with the Copyright Transfer Agreement signed between the authors and the American Society of Civil Engineers (ASCE)

the current practices would be easier than agree on substantially changing them. In these cases, although entirely modifying the course of action may offer higher gains than building on top of the current one, it would be more difficult to implement in reality.

4.1. 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. It involves researchers and experts (system operators). The key idea is to treat 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, rather than to replace their judgment. The methodology described here should be adapted to each specific case study, if required, in order to match its specific features. The methodology has two main parts (Fig. 4.1):

- The definition of the operating rules, integrating expert knowledge and optimization results. FRB systems are used to represent the implicit operating rules followed in the current *modus operandi* of the system, linking state variables with decision variables. Results from an optimization algorithm can be used to further improve the seasonal operation of the system. In this case, the optimized time series of results are used in conjunction with expert knowledge.
- An inflow forecasting system, in which the meteorological and hydrological information available is used to predict inflows for the following time periods (days, months, etc.). This part may be omitted if the system operation uses externally-obtained inflow forecasts.

From the preliminary meetings, in which the system and its operation are discussed, the two parts are developed in parallel and then integrated into the DSS. The optimization model should also be built in a collaborative process, in order to guarantee that it possesses the features desired by the system operators.

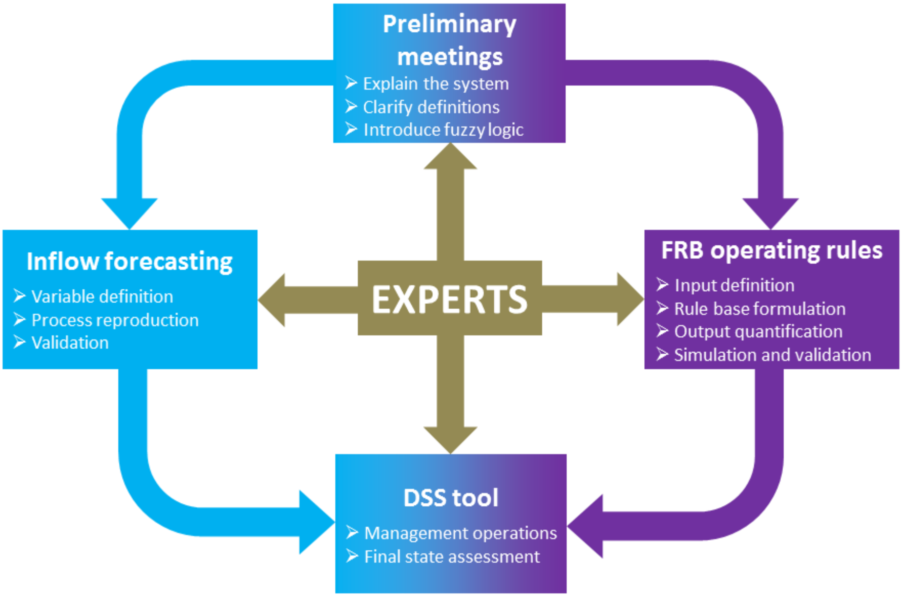


Fig. 4.1: Framework for combining expert knowledge with fuzzy logic

4.1.1. Preliminary meetings

The preliminary meetings aim at building confidence between experts and modelers, as well as to agree in a common and clear picture of the system and the decision-making processes. More specifically, these meetings have three main objectives:

1. Obtain a clear picture of how the system is actually managed, as explained by the system operators: goals, physical constraints, legal constraints, auto-imposed constraints, decision-making process, etc. Modelers should not be biased by their own knowledge of the system when collecting the experts' information.
2. Introduce fuzzy logic to the experts stating its foundations, how a FRB works in general, the way it is intended to be applied to the case study and the role experts' will play during the process.
3. Agree on the definitions of the key concepts that are going to be used, such as *low storage*, *normal operation*, *drought*, etc. Precise definitions should be given and they should remain steady during the whole process.

4.1.2. FRB operating rules

Fuzzy rule-based (FRB) systems are used for the definition of the implicit operating rules currently followed. This process combines the stages described in subsection 2.2.1 with the techniques summarized in subsection 2.2.3. The main FRB features and outputs are decided through interaction with the system operators and validated against historical records to ensure they reproduce the current operation of the system. The merge between expert judgment and optimization algorithms proposed is sequential: 1) operating rules are defined, tested and validated using expert knowledge (as done in Macian-Sorribes and Pulido-Velazquez, 2017); and 2) the optimization results are used to modify the rules created to improve them.

The first decision consists in establishing the number of FRB systems to use. Situations in which it is advisable to use more than one are, for example, decision-making processes in which more than one group of operators or stakeholders are involved (each FRB should reproduce the behavior of a single group), and sequential decision-making processes (in which the output of one stage is used as input for the next one). Afterwards, expert knowledge is needed in setting the structure of the FRB systems (number of input variables, number of classes for each variable, number of rules and number of outputs) and quantifying the variables to be used (membership functions for the inputs and membership functions or non-fuzzy values for the outputs).

Once this is done, it is important to validate these FRB systems comparing them with the reference behavior (e.g. historical records for the case of reproducing the current decision-making). This stage can be supported by a simulation model, in which the operating rules are introduced to obtain time series of variables (storages, demand deliveries, turbined flows, streamflows and so on). If validation is not adequate, the build-up process should be re-started.

4.1.3. Inflow forecasting

Although inflow forecasting is independent from the reservoir operating rules, it is usually part of decision-making processes if future inflow scenarios are estimated by the decision-makers. If the goal is just the estimation of operating rules, or if inflow forecasts are obtained from external sources, this stage can be skipped. However, if the analysis aims at giving the system operators a DSS tool able to mimic their decision-making processes, the inflow forecasting mechanisms used should be included or, if obtained externally, they should be added as inputs of the decision-making process.

Inflow forecasting mechanisms, in general, do not rely on expert knowledge as operating rules do. In case it is used, it can be reproduced using the same FRB systems as pointed out for the operating rules, or modeled using another technique like fuzzy regression (Macian-Sorribes and Pulido-Velazquez, 2017).

4.1.4. DSS for seasonal multireservoir management

The development of the DSS tool requires merging the inflow forecasting mechanisms and the FRB systems representing the reservoir operating rules. The aim is to reproduce the decision-making process to obtain suitable operation decisions using the inflow projections and the initial state of the system.

In this stage, it is very important to agree with the experts on the way in which results should be provided by the tool (a single decision, a set of alternatives, a probabilistic description and so on), as well as how should them be visually presented. This will depend on both the character of the inflow forecasts (deterministic, probabilistic, fuzzy and so on) and the operators' desires (for example, some operators feel familiar with probability distributions while others refuse them).

4.1.5. Integration of optimization results

This stage should be developed after the validation of the expert-based operating rules. It consists in building on top of the current processes, defining improvements while maintaining the essence of the current *modus operandi*. The optimization model to be used in this stage should be developed in close collaboration with the operators in order to match, as much as possible, their vision of the system and the constraints that apply to its management. After running the model, the optimal decision time series obtained should be retrieved and sorted in order to embed them into the FRB systems. The variables to introduce depend on how the operating rules are defined based on expert knowledge.

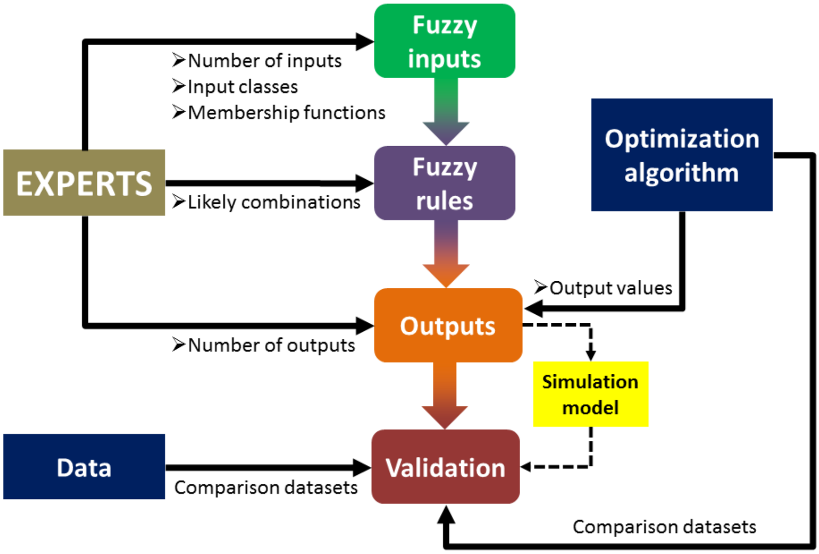


Fig. 4.2: Combination of optimization algorithms and expert knowledge when building FRB systems reproducing optimal rules

In order to keep a similar FRB structure and the system operators' perception of the state of the system (estimated through the fuzzy inputs and rules), the combination of sources proposed affects exclusively the outputs of the FRB systems (Fig. 4.2). It consists in replacing (totally or partially) the output quantifications provided by the experts by the results of the optimization algorithm. In any case, this replacement should be done after evaluating carefully the optimization results, as well as contrasting how different they are from the expert-based outputs. In this way, changes due to the optimization algorithm would not substantially modify the current decision-making stages.

The ways to introduce the optimization results into the outputs of the FRB systems are the same as reported in the literature for historical values (Bai and Tamjis, 2007; Dubrovin et al., 2002; Shrestha et al., 1996) or optimization results (Mousavi et al., 2005; Panigrahi and Mujumdar, 2000; Russell and Campbell, 1996). One remarkable difference is that, in this case, the purpose of the validation is to compare the obtained rules with the ones built using exclusively expert knowledge, as well as with the results from an optimization algorithm if desired. In order to validate the optimal operating rules, their performance should be superior to the ones built solely with expert knowledge. However, they will usually not reach the efficiency level of the optimal decisions obtained by the stochastic programming algorithm.

4.2. STIG TOOL

In parallel to the development of the ESPAT tool, the *Simulation Tool in GAMS* (STIG) tool has been created to perform runs subject to pre-defined rules and policies, with the possibility to embed FRB systems representing operating rules within its structure. The same interface scheme and features as the ESPAT tool are used, with the addition of the mathematical representation of the operating rules to be employed in the simulation. STIG implements two modules, each one of them assuming a different rule form: STIG_ZB and STIG_FRB.

4.2.1. STIG user interface

ESPAT and STIG share the same interface, so a system model created to be run with ESPAT can also be run with STIG and vice versa. The only additional inputs required by STIG are the parameters required to define and quantify the operating rules desired. These parameters are described in the following subsections.

4.2.2. STIG_ZB

STIG_ZB defines the operating rules through a system of priorities attached to each water use and reservoir, being the latter divided into zones with different priorities attached. These priorities are inputs of the model, and should be specified by the user. They are weighting factors that guide water allocation: the higher the priority is, the earlier the corresponding demand will be delivered or the corresponding reservoir will be refilled. By dividing the reservoirs into zones with different priorities, one can reproduce operating rules as the rule curves or the zone-based operating rules (Lund, 1996; Lund et al., 2017; Lund and Guzman, 1999). The parameters that the user needs to introduce through the interface are the zones in which each reservoir is divided and the priorities attached to demands and reservoir zones.

This use of priorities is similar to other DSS shells. The purpose of STIG_ZB is not to act as an independent DSS; but to compare ESPAT's results with the ones obtained using pre-defined rules, taking advantage of having the same interface. For this, there is no need to use an external DSS and introduce the same inputs twice.

Mathematically, the STIG_ZB code performs each time stage an optimization procedure to maximize the total priority obtained through water allocation (Fig. 4.3):

$$TP(t) = \sum_{n,n'} P(t)_{n,n'} \cdot mQ(t)_{n,n'} + \sum_{d} P(t)_d \cdot C(t)_d + \sum_{hpp} P(t)_{hpp} \cdot T(t)_{hpp} + \sum_{e} \sum_{z} P(t)_{z,e} \cdot S(t)_{z,e} \qquad \mathbf{4.1}$$

Where *TP(t)* total priority; $P(t)_{n,n'}$ priority associated with the environmental flow at the *n-n'* stream; $mQ(t)_{n,n'}$ environmental flow through *n-n'*; $P(t)_d$ priority associated with demand *d*; $C(t)_d$ water delivered to *d*; $P(t)_{hpp}$ priority associated with hydropower plant *hpp*; $T(t)_{hpp}$ turbined flow by *hpp*; $P(t)_{z,e}$ priority associated with water stored in zone *z* of reservoir *e*; and $S(t)_{z,e}$ water stored in zone *z* of reservoir *e*.

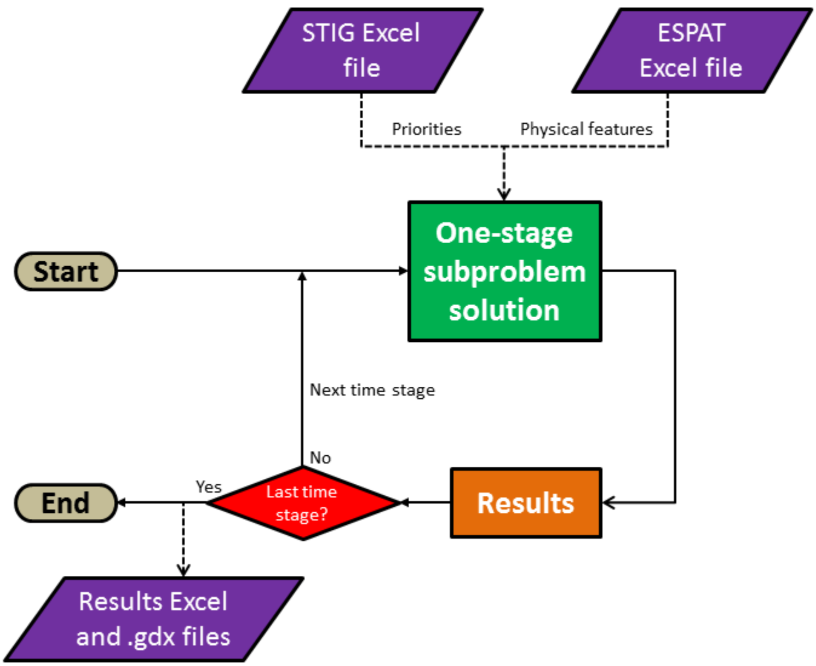


Fig. 4.3: STIG_ZB code general flowchart

4.2.3. STIG_FRB

STIG_FRB includes the operating rules as FRB systems. The same priority schemes and total priority calculations of STIG-ZB are used. Mathematically, the FRBs are introduced as constraints that condition the maximum amount of water delivered to each demand and/or the amount of water released from each reservoir, unless there is not enough resource or additional spills are required for safety reasons (Fig. 4.4).

The parameters that the user needs to introduce are the same as for STIG_ZB, with the addition of the information required to build the FRB systems (number of fuzzy inputs, number of fuzzy rules, number of fuzzy outputs, and the quantifications associated with the inputs and outputs).

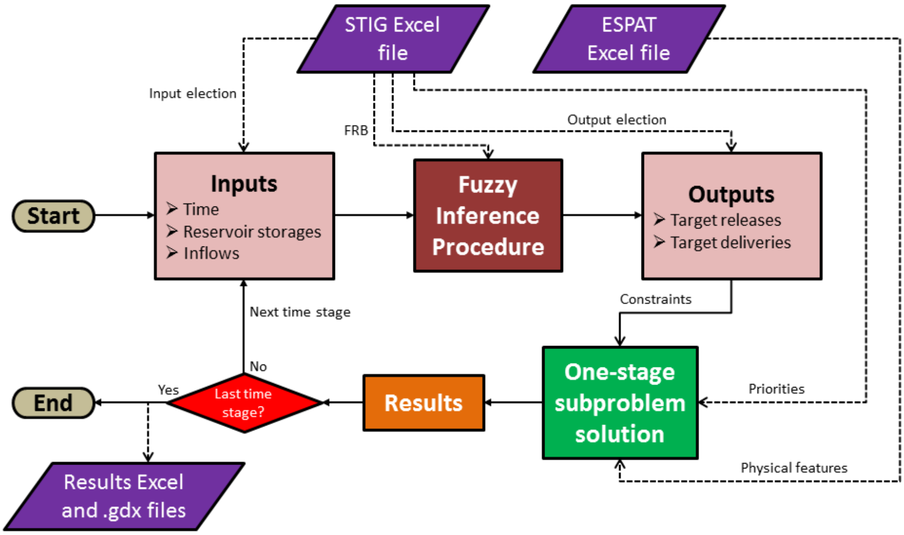


Fig. 4.4: STIG_FRB code general flowchart

5. CASE STUDY: THE JUCAR RIVER BASIN IN SPAIN

The Jucar river basin has been, for decades, the most used case study in the research carried out by the Universitat Politècnica de València (UPV). This is not only due to its physical proximity to the city of Valencia, but also because of the specific features of the river. The Mediterranean hydrology, the high demands in comparison to the resource, the regional conflicts caused by the share of water, the growth of environmental issues during last decades, the exploitation of groundwater bodies and so on, make the management of the Jucar river a true challenge.

This Chapter refers exclusively to the presentation of the case study features and information sources used to develop the models. The models built in the applications of the methodologies developed in this PhD thesis are described in subsequent chapters.

5.1. CASE STUDY DESCRIPTION

Covering 22,261 Km^2, the Jucar is one of the most important rivers in Eastern Spain (Fig. 5.1). It starts at the Iberica mountain range, besides the San Felipe hill, at 1,585 m height. The river flows along the Cuenca, Albacete and Valencia provinces until it meets the Mediterranean Sea. The annual precipitation ranges between 309 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, and 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 is provided by groundwater outflow through springs and stream–aquifer interaction.

The main regulation facilities are the reservoirs of Alarcon (1,088 Mm^3 useful storage), Contreras (429 Mm^3), and Tous (369 Mm^3). There are eight additional reservoirs with useful storage greater than 1 Mm^3, mainly devoted to hydropower (CHJ, 2013). The main aquifers are the Mancha Oriental (located in the surroundings of Albacete), which holds the majority of the groundwater-irrigated demands and shares a strong stream-aquifer interaction with the Jucar river; the Plana de Valencia Sur (in the lower basin of the river), hydraulically connected to the Jucar river and the l'Albufera lake; and the Hoces del Cabriel (downstream Contreras) which receives the seepage losses from the reservoir and returns them to the Jucar river several kilometers downstream.

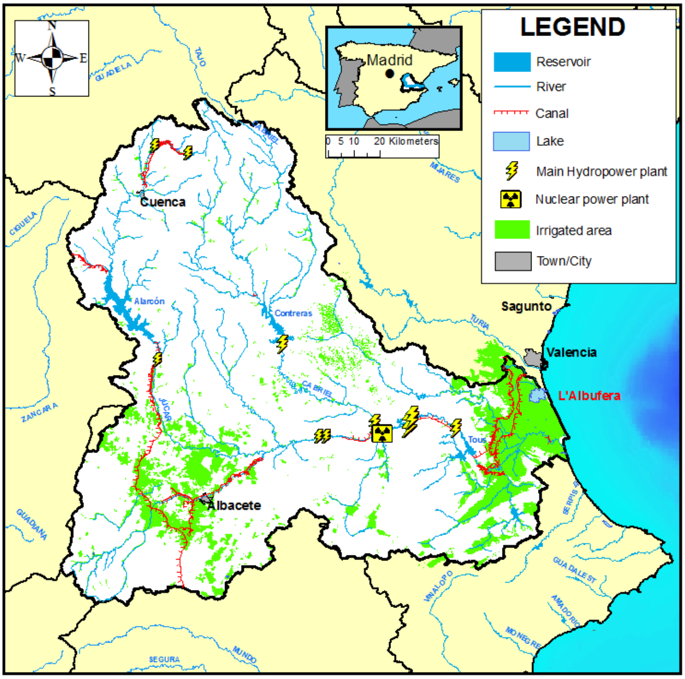


Fig. 5.1: Jucar river basin location map

The annual mean consumptive demand in the Jucar river system is 1,505 Mm^3/year for the 2009–2015 period (CHJ, 2013). 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 found in the lower basin and 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. The Jucar river system 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).

The upper basin, upstream the Alarcon reservoir, is characterized by the absence of important water abstractions (with the exception of the Cuenca city supply), and a continuous aquifer discharge to the river due to natural springs and stream-aquifer interaction.

The middle basin, between Alarcon and Tous, can be divided in two: the Mancha Oriental plain and the Caroig massif. Once it lefts Alarcon, the river flows through the Mancha Oriental plain above Miocene-Pliocene permeable limestones with conglomerate intercalations. This plain is a former endorheic zone connected to the Jucar river in the 19th century by the Maria Cristina Canal. The underlying Mancha Oriental aquifer discharged to the Jucar river until the massive groundwater abstractions started in the 1970's lowered its level, moving the Jucar river from a gaining to a losing river.

After the small Molinar reservoir, the Jucar river enters the Ayora valley, a small Triassic clay emergence that separates the Mancha Oriental plain from the Caroig massif. The latter is a Cretaceous sandstone aquifer which discharges a considerable amount of water to the river via springs and stream-aquifer interaction. This discharge is added both upstream (via the Jucar and the Escalona rivers) and downstream (through the Jucar and the Sellent rivers) of Tous. The most important tributary is the Cabriel, river, whose resources are regulated by the Contreras reservoir.

Downstream Tous, the Jucar river enters its lower basin, flowing over the Valencia plain, a Quaternary aquifer in which gravel, sand, mud and clay alternate. Its discharge is shared between the Jucar river and the l'Albufera lake, an environmental protected area and an icon for the Valencia city and region. The landscape is an immense floodplain that holds the majority of the river-irrigated crops, existing some of them since the Middle Age. The main tributaries of the Jucar river are the Sellent, Albaida and Magro rivers. The river meets the Mediterranean Sea 30 Km south of Valencia.

5.2. SYSTEM'S OPERATION

Given the Jucar river features previously outlined, its management is subject to a considerable amount of physical, environmental and legal constraints. Furthermore, management practices have created non-written constraints product of tradition. The physical constraints correspond to the reservoir, river streams and canals capacity, as well as the daily refill or drawdown maximum rates that need to be followed at Tous, since it has a rock-fill dam. The environmental constraints are the minimum flows implemented in the basin, whose supply is made prior to any other system delivery. Today's main legal constraint is the Alarcon Agreement, described in the following subsection.

5.2.1. The Alarcon Agreement

The Alarcon Agreement was signed in July 23th 2001 between the Spanish Ministry of Environment and the *Unidad Sindical de Usuarios del Jucar* (Jucar Users Union, USUJ), in order to integrate the USUJ-owned Alarcon reservoir into the Jucar river basin management strategy. While retaining the legal property, USUJ gave the CHJ the right to manage the reservoir as long as the Agreement stipulations were fulfilled. Among them, the most important regarding water management is the division of Alarcon in two zones by a rule curve (Fig. 5.2).

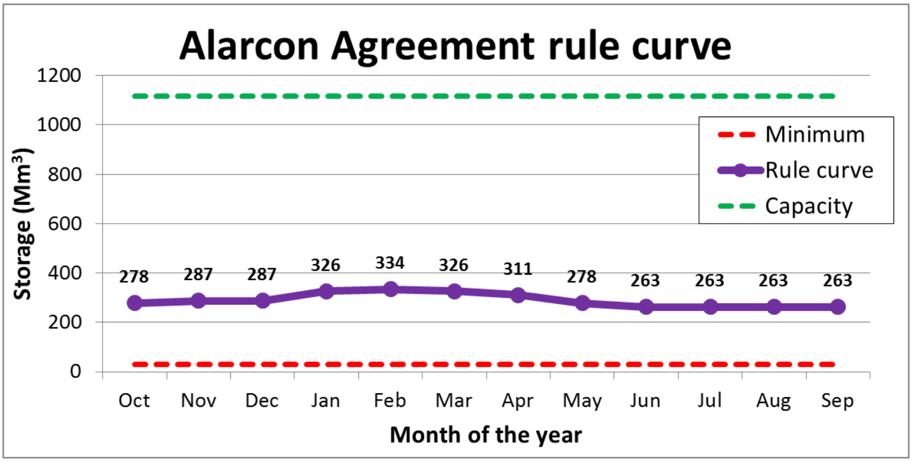


Fig. 5.2: Rule curve established by the Alarcon Agreement for the Alarcon reservoir

If the storage in Alarcon is above the curve, water can be freely allocated. However, if it is below the curve, then water is reserved to the USUJ members, being not possible to allocate any resource, from Alarcon or any other reservoir, to non-USUJ users. Water would be allocated to non-USUJ users under these circumstances if and only if they agree to pay USUJ a financial compensation equal to the cost of the alternative sources (pumping wells and so on) used by USUJ to meet its demands.

5.2.2. *Seasonal operation*

Shaped by the physical, environmental and legal constraints, the operation of the Jucar river system is made by the Jucar River Basin Management Authority (CHJ) Operation Office (in Spanish *Oficina de Explotación*) and the Jucar River Reservoir Releases Commission (with members of the CHJ, municipalities, farmers, industries, etc.; in Spanish *Comisión de Desembalse*). The following description of the seasonal decision-making process and criteria in the Jucar river system was the result of a collaborative process summarized in Macian-Sorribes and Pulido-Velazquez (2017).

The most important management decisions are made between May and September, the irrigation season, in which the agricultural demands of the system concentrate. For this season, the CHJ Operation Office predicts future inflows between May and September using a deterministic forecast method based on inflows during the last months, precipitation projections for the next months, rainfall in past months and the expert knowledge of the system managers. These inflows, as well the resource available in the reservoirs, are used to estimate how much water should be delivered to the users. It is discussed, modified if required and approved by the Reservoir Releases Commission (Macian-Sorribes and Pulido-Velazquez, 2017). After its approval, the Operation Office establishes the amount of water to be released from Alarcon, Contreras and Tous in order to guarantee the committed deliveries. Then, the Operation Office determines a release plan that is monitored, controlled and modified if required on a daily basis.

The criteria employed in the Jucar river seasonal operation, as explained by the CHJ Operation Office, are the following:

- Avoid undesired spills from Tous as much as possible.
- Not storing more than approximately 450 Mm^3 in Contreras, as stability problems have been found in its secondary dam (Collado).
- Not storing more than approximately 80 Mm^3 in Tous at the end of September to avoid potential floods in autumn.
- Not storing less than 40 Mm^3 or so in Tous, as it would give the impression that the supply to Valencia is endangered (people without further knowledge on the Jucar river system may think Tous is the only supply source to Valencia).

- Avoid as much as possible to fall below the rule curve defined by the Alarcon Agreement.
- Balance Alarcon and Contreras storages.

During the irrigation season the Reservoir Releases Commission meets regularly to re-schedule deliveries if required. Out of this season, the operating rules are easier, as agricultural demands are low and water flows tend to be higher. In this season, reservoir releases correspond to the minimum rates established (large enough to fulfill the few winter agricultural demands), the ecological flows and the urban water supply deliveries.

Considering the other consumptive reservoirs of the system, Forata is used by the Magro river users, with no water left for the Jucar ones unless the Magro flows are very high; while Bellus' regulation capacity, around 15 Mm^3/year, is negligible in comparison with the total Jucar river demand. With regard to hydropower, no release is made from Alarcon and Contreras solely for power production. Therefore, hydropower plants and hydropower-devoted reservoirs are committed to turbine exclusively the water releases arranged for consumptive purposes. On the other hand, the power company owning the hydropower reservoirs is allowed to freely manage them as long as they do not interfere with the CHJ policies. In addition, the water stored in these reservoirs is not required to meet any demand unless there is not enough water available in the rest of the system.

5.3. DATA AND MATERIALS

A detailed description of the main features of the Jucar river system is given in Appendix A1. It has been based on the Jucar River Basin Management Plan for the 2009-2015 period (CHJ, 2013), complemented by several master and PhD thesis properly cited. Although a new Plan has been developed for the 2015-2021 period, the system description and features of the 2009-2015 plan match the analysis period considered (1998-2013). Specific Jucar river studies used were properly cited. The GIS files employed in the figures were downloaded from the Spanish Ministry of Agriculture, Food and Environment (http://servicios2.magrama.es/sia/visualizacion/descargas/mapas.jsp) and the download page provided by the Jucar River Basin Management Authority (CHJ, http://aps.chj.es/down/html/descargas.html).

6. APPLICATION 1: IMPROVING CONJUNCTIVE USE OF SURFACE AND GROUNDWATER IN THE JUCAR RIVER SYSTEM[3]

The CSG-SDDP algorithm has been applied to the Jucar river system focusing on improving conjunctive use operations in order to enhance the economic performance of the system. It has been chosen due to its lack of perfect foreknowledge of future inflows, its suitability to be applied to large-scale water resource systems, and the capability of the CSG-SDDP algorithm to model stream-aquifer interaction and to consider it when obtaining optimal decisions. This last issue is decisive given the interaction between the Jucar river and the Mancha Oriental aquifer.

The monthly time scale has been chosen. Given that some aquifers have a slow hydraulic response, requiring some time to notice the impacts of a change in pumping rates (being the case of the Mancha Oriental aquifer), the time horizon of the model has been enlarged up to fifteen years. This length is also in line with the hydrological characteristics of the Jucar River Basin, subject to multiannual droughts.

Three main aquifers interact with the Jucar river and play a distinct role in its management. The largest is the Mancha Oriental aquifer, with 7.145 Km^2 of extension. Being hydraulically connected to the Jucar river, the intense irrigated land development since the 1970s has led to a significant drop in groundwater tables. This issue has provoked a remarkable streamflow depletion due to stream-aquifer interaction (Sanz et al., 2011).

The remaining two aquifers are Hoces del Cabriel, underneath Contreras, which returns its seepage losses to the Cabriel river downstream; and Plana de Valencia Sur, located in the lower basin, mined for agricultural purposes

[3] The model description and result presented in this chapter have been adapted from Macian-Sorribes et al., (2017). Its use complies with the Copyright Transfer Agreement signed between the authors and the American Geophysical Union (AGU)

during droughts. All of them share some kind of hydraulic connection with surface waters, so stream-aquifer interactions should be taken into account due to its possible role in improving the efficiency of the Jucar river system.

6.1. MODELING STREAM-AQUIFER INTERACTION IN MANCHA ORIENTAL

The most relevant stream-aquifer interaction takes place between the Jucar river and the Mancha Oriental (MO) aquifer. An embedded multireservoir model (EMM) with two linear reservoirs has been developed to reproduce it. Its calibration has been based on the Jucar river streamflow records across the boundaries of the MO aquifer (stations 08129 and 08144, Fig. 6.1) obtained by CEDEX (2013), the pumping rates estimated by remote sensing (Castaño et al., 2010; Sanz et al., 2011, 2009) and the simulated time series of natural net groundwater discharge. The latter were obtained in previous CHJ studies by calibrating a groundwater flow simulation model against historical records and then removing the anthropic actions from it.

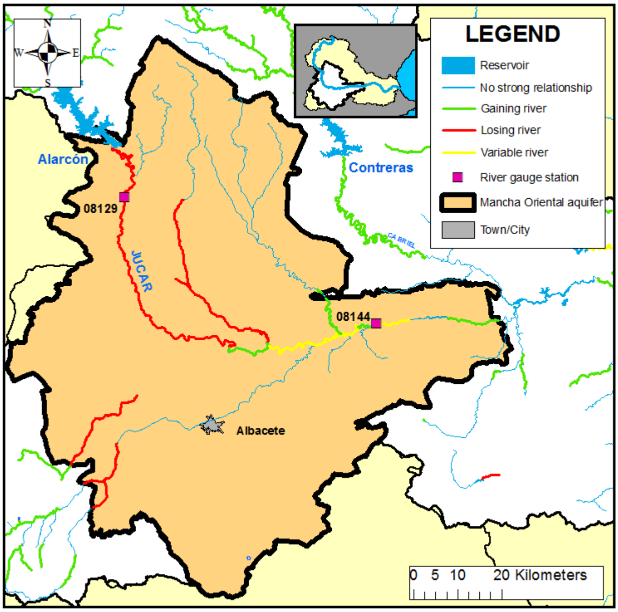


Fig. 6.1: Mancha Oriental stream-aquifer interaction and location of gauging stations

Since the natural discharge of the aquifer is already available, there is no need to include natural actions in the EMM, since the principle of superposition (section 3.3) can be applied. The Mancha Oriental aquifer fulfills the requirements of this principle given that groundwater head variations (up to 10 m) are not significant in comparison with the thickness (200 m at least). The EMM has been built to represent the impacts of anthropic actions on stream-aquifer interaction, which will be added to the natural discharge by the water resources management model (which includes natural stream-aquifer interaction in the natural inflow time series).

The anthropic impacts on the stream-aquifer interaction (X_t^{aqr} in Eq. 3.12), can be calculated as the historical stream-aquifer response less the natural one. The historical behavior can be estimated as the difference between the downstream (08144) and upstream (08129) discharge records, since surface runoff is negligible except after exceptional rainfall events (Sanz et al., 2011). The anthropic actions (net recharge) are the agricultural percolation minus the groundwater abstractions. The EMM (Eqs. 3.11 to 3.13) was fitted to reproduce the time series of anthropic impacts on stream-aquifer interactions using a least-square fitting process (Fig. 6.2).

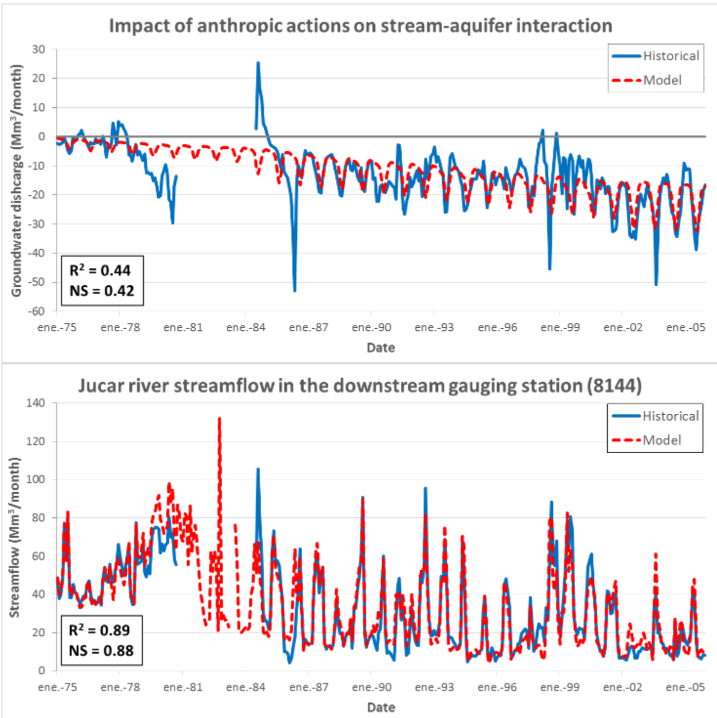


Fig. 6.2: Goodness of fit of the EMM of the Mancha Oriental stream-aquifer interaction

The two discharge parameters α^{aqr} obtained have been 3.94 and 0.0055 months^{-1}. The stress allocation coefficients b^{aqr} have been estimated as 0.18 and 0.82 respectively (18% of the recharge and pumping from the first linear reservoir and 82% from the second). Negative values on the impact of anthropic actions indicate a decrease in the aquifer discharge due to pumping. The fitted EMM captures both the seasonal and the long-term evolution of the anthropic impacts. There are periods in which it departs from the historical records (e.g. 1977-1980 and 1997-2000), although the impact on the downstream flow records is limited. It can be considered that the fitted EMM is able to adequately reproduce the anthropic impacts on the stream-aquifer interaction.

6.2. CONJUNCTIVE USE OPTIMIZATION MODEL OF THE JUCAR RIVER

A hydroeconomic conjunctive use model has been developed to explore strategies to improve the operation of the Jucar river system considering the stream-aquifer interactions. It consists of 27 nodes, 8 surface reservoirs, 5 EMMs, 7 sub-basins, 18 consumptive demands, 9 hydropower plants and 6 environmental flows (Fig. 6.3). The CSG-SDDP has been used to obtain optimal management decisions for both surface and groundwater resources. The goal of the stochastic optimization is to maximize the net total benefits (current plus expected).

The physical features of the model have been obtained from CHJ (2013), being described in detail in Appendix A2. Apart from the environmental minimum flows, the model also takes into account the preservation of the l'Albufera lake, the most important water-dependent ecosystem found, whose main inflows are the surface returns from the demands of rice agriculture. To preserve this ecosystem in the model, the supply to the rice demands was considered a constraint, maintaining at least the same supply levels than the current operation.

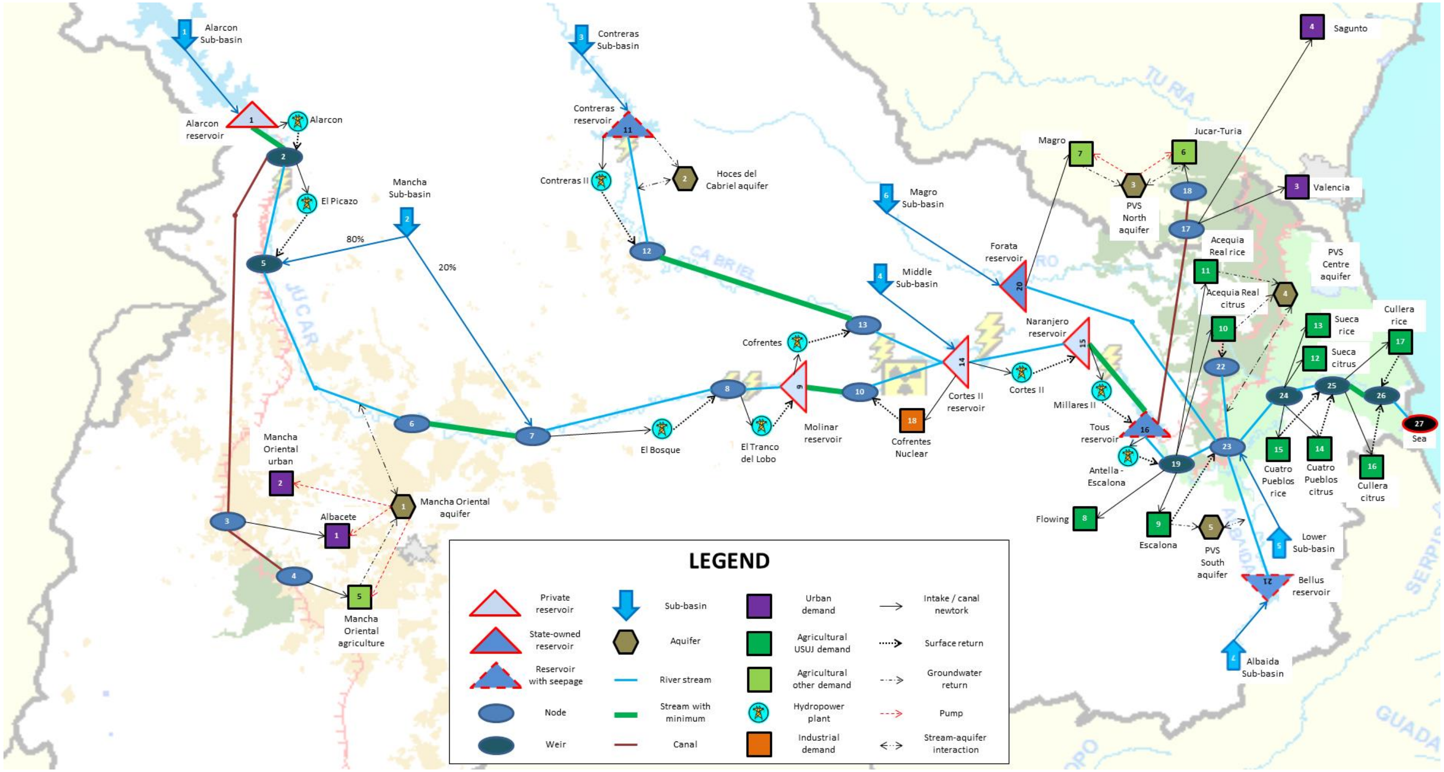


Fig. 6.3: Jucar river system conjunctive use model network flow

Urban demand curves were estimated using the point expansion method (Harou et al., 2009; Jenkins et al., 2004), using as base the data reported in a study carried out by Pulido-Velazquez et al. (2006b). The same information source obtained agricultural demand functions using Positive Mathematical Programming (PMP, Howitt 1995), employing data from previous studies (MMA, 2004; Sumpsi et al., 1998). Energy prices between 1998 and 2012 were obtained from CHJ (2013). A demand function for the Cofrentes nuclear power plant was estimated assuming that the marginal value of water is equal to the total benefits (production times prices) divided by the demand.

6.3. PRIORITY-BASED SIMULATION MODEL

A simulation model has also been developed to compare the optimization results with the ones from the current operation. It has been built using STIG_ZB (subsection 4.2.2), trying to mimic the historical operation of the system. The flow network is the same as for the optimization model. However, economics does not drive water allocation; instead, resource is delivered based on the priorities attached to the different demands and uses, calibrated to reproduce the historical operation of the system. The priorities adopted and the calibration results appear in Appendix A2. It has been successful in the majority of the system and, especially, in the downstream part, so it offers a good representation of the current operation of the Jucar river. After the simulation has been run, the economic demand functions have been used to obtain the economic benefits for the given deliveries.

6.4. RESULTS AND DISCUSSION

6.4.1. System performance

The model results consist of surface and groundwater allocations, streamflows, turbined flows, energy produced, economic benefits and stream-aquifer interactions. These results have been obtained for both the current operation and the stochastic optimization during the 1998-2013 period (Table 6.1). Results regarding demand deliveries and benefits are presented aggregating them by type of demand and spatial proximity. Tables showing separately each demand, as well as the corresponding graphs, are provided in Appendix A2.

Table 6.1: Average performance results per alternative for the 1998-2013 period

	Category	Consumptive uses					Hydropower	Environment	Systemwide level	
	Type	Urban		Agricultural[1]			Totals	Mancha Oriental aquifer discharge[2]	Urban	Agriculture
	Variable	Mancha	Valencia	Mancha	USUJ	Jucar-Turia & Magro				
Current system management	Surface deliveries (Mm^3)	14.33	114.51	16.96	540.60	29.49	-	-	128.84	587.05
	Groundwater deliveries (Mm^3)	16.10	0.00	315.45	0.00	73.10	-	-	16.10	388.55
	Energy produced (GWh)	-	-	-	-	-	372.20	-	-	-
	Economic benefits (M€)	60.26	228.78	78.89	63.37	51.65	22.26	-	289.04	193.91
	Groundwater discharge (Mm^3)	-	-	-	-	-	-	-63.31	-	-
Stochastic programming	Surface deliveries (Mm^3)	13.64	114.51	29.13	556.73	42.13	-	-	128.15	623.17
	Groundwater deliveries (Mm^3)	16.79	0.00	238.30	0.00	59.99	-	-	16.79	303.11
	Energy produced (GWh)	-	-	-	-	-	414.03	-	-	-
	Economic benefits (M€)	60.36	228.78	78.34	65.83	52.21	25.00	-	289.14	196.38
	Groundwater discharge (Mm^3)	-	-	-	-	-	-	-29.91	-	-
Differences	Surface deliveries (Mm^3)	-0.70	0.00	12.17	16.14	12.64	-	-	-0.70	36.13
	Groundwater deliveries (Mm^3)	0.70	0.00	-77.14	0.00	-13.11	-	-	0.70	-85.44
	Energy produced (GWh)	-	-	-	-	-	41.83	-	-	-
	Economic benefits (M€)	0.10	0.00	-0.55	2.45	0.56	2.73	-	0.10	2.46
	Groundwater discharge (Mm^3)	-	-	-	-	-	-	33.40	-	-

[1]: not including the economic benefits of rice demands

[2]: a negative value implies a net aquifer recharge by rive seepage

The majority of the variables analyzed show similar performance levels. This is due to the current operating rules being product of a long management experience and intense negotiation processes. The stochastic programming does not oppose the current operation, but suggests some modifications to further improve its economic benefits.

The stochastic programming reduces groundwater abstractions due to agricultural purposes in the Mancha Oriental aquifer by around 80 Mm^3/year, although the net benefits are only diminished by 0.55 M€/year (0.7% of the total benefits). Less pumping increases the streamflow downstream the aquifer, due to stream-aquifer interaction, around 33 Mm^3/year. This additional resource substantially contributes to the preservation of the environmental flow downstream of the Alarcon reservoir during drought periods. It also provides additional resources for the downstream agricultural demands, which are curtailed when surface water is scarce. The economic benefits in the lower Jucar demands grow by 3 M€/year, six times greater than the loss of revenue experienced in the Mancha Oriental aquifer demands. Part of the success of this tradeoff is caused by the aquifer storage recovery, which lowers the pumping costs. The increase in surface water availability also results in higher surface deliveries to the Mancha Oriental area, as counterpart for the decrease in pumping.

Stochastic programming improves hydropower production by 42 GWh/year, 11% of the total current value. This is due to the stream-aquifer interaction in the Mancha Oriental, whose increased discharge benefits the downstream hydropower plants. Furthermore, the operation done by stochastic programming uses Tous as the tail reservoir of the system instead of Naranjero, as shown in the operation analysis in the next subsection. Hydropower benefits rise by 2.75 M€/year, 12% higher. The slight difference between production and benefits is due to a better scheduling of hydropower according to the monthly energy price. CSG-SDDP provides a systemwide benefit increase of around 5.25 M€/year, 1% of the total net returns with the current operation. However, the reduction of the Mancha Oriental aquifer pumping adds robustness and resiliency against droughts.

Table 6.2 shows the system performance during the 2005-2008 drought for both alternatives.

Table 6.2: Average performance results per alternative for the 2005-2008 drought period

	Category	Consumptive uses					Hydropower	Environment	Systemwide level	
	Type	Urban		Agricultural[1]			Totals	Mancha Oriental aquifer discharge[2]	Urban	Agriculture
	Variable	Mancha	Valencia	Mancha	USUJ	Jucar-Turia & Magro				
Current system management	Surface deliveries (Mm^3)	6.94	114.51	0.00	439.72	5.71	-	-	121.45	445.43
	Groundwater deliveries (Mm^3)	23.49	0.00	332.41	0.00	96.88	-	-	23.49	429.29
	Energy produced (GWh)	-	-	-	-	-	278.04	-	-	-
	Economic benefits (M€)	59.84	228.78	77.89	53.24	50.54	16.59	-	288.62	181.67
	Groundwater discharge (Mm^3)	-	-	-	-	-	-	-92.43	-	-
Stochastic programming	Surface deliveries (Mm^3)	10.67	114.51	17.47	509.62	29.67	-	-	125.18	553.36
	Groundwater deliveries (Mm^3)	19.76	0.00	213.78	0.00	72.42	-	-	19.76	289.60
	Energy produced (GWh)	-	-	-	-	-	326.30	-	-	-
	Economic benefits (M€)	60.15	228.78	71.03	64.13	51.68	19.64	-	288.93	186.84
	Groundwater discharge (Mm^3)	-	-	-	-	-	-	-45.33	-	-
Differences	Surface deliveries (Mm^3)	3.74	0.00	17.47	69.90	23.96	-	-	3.74	107.93
	Groundwater deliveries (Mm^3)	-3.74	0.00	-118.63	0.00	-24.46	-	-	-3.74	-139.69
	Energy produced (GWh)	-	-	-	-	-	48.26	-	-	-
	Economic benefits (M€)	0.31	0.00	-6.86	10.90	1.13	3.04	-	0.31	5.17
	Groundwater discharge (Mm^3)	-	-	-	-	-	-	47.09	-	-

[1]: not including the economic benefits of rice demands

[2]: a negative value implies a net aquifer recharge by rive seepage

Comparing it with the results for the whole period, different management strategies against droughts can be found. The current operation treats surface and ground waters in isolation, so the main management option applied consists in replacing the surface water scarcity by increasing groundwater pumping. The Mancha Oriental abstracts 24 Mm^3/year more than the whole period (on average), inducing a reduction of 29 Mm^3/year due to stream-aquifer interaction.

On the contrary, stochastic optimization implements a joint management of surface and ground waters. It reduces groundwater pumping by 22 Mm^3/year instead of increasing it, causing a rise in the stream-aquifer interaction around 47 Mm^3/year compared with the current operation. This higher surface flows rise the surface water allocations to agricultural demands: from a 140 Mm^3/year curtailment to a 71 Mm^3/year reduction. Concerning economic variables, the Mancha Oriental irrigation district suffers the worst impact in the optimal operation, changing from losing 1 M€/year to 7 M€/year. However, this loss is compensated by increased downstream demand allocations, whose loss of 11 M€/year is reduced to 2.5 M€/year. Hydropower suffers similar impacts in both alternatives, losing 6 M€/year. It can be concluded that stochastic programming enhances the system performance due to a proper management of the stream-aquifer interaction between the Mancha Oriental aquifer and the Jucar river.

6.4.2. Reservoir operation

The monthly storages in the main reservoirs (Alarcon, Contreras and Tous) were analyzed to compare the operation strategies (Fig. 6.4). The rest of the reservoirs have very little impact on the system performance due to its low capacity (Molinar, Forata and Bellus) or reduced live storage due to hydropower operation (Cortes II and Naranjero). This comparison has been done using box-whisker plots, showing the mean (small circle) and the quantiles for the analysis period (1998-2013). The Alarcon reservoir, with the greatest useful capacity, is operated in a similar way in both alternatives, consisting in providing carryover storage to move water from wet to dry years. This can be determined by the absence of outliers and the smooth refill-drawdown cycle, although the stochastic programming shows a clearer intra-annual pattern between February and June.

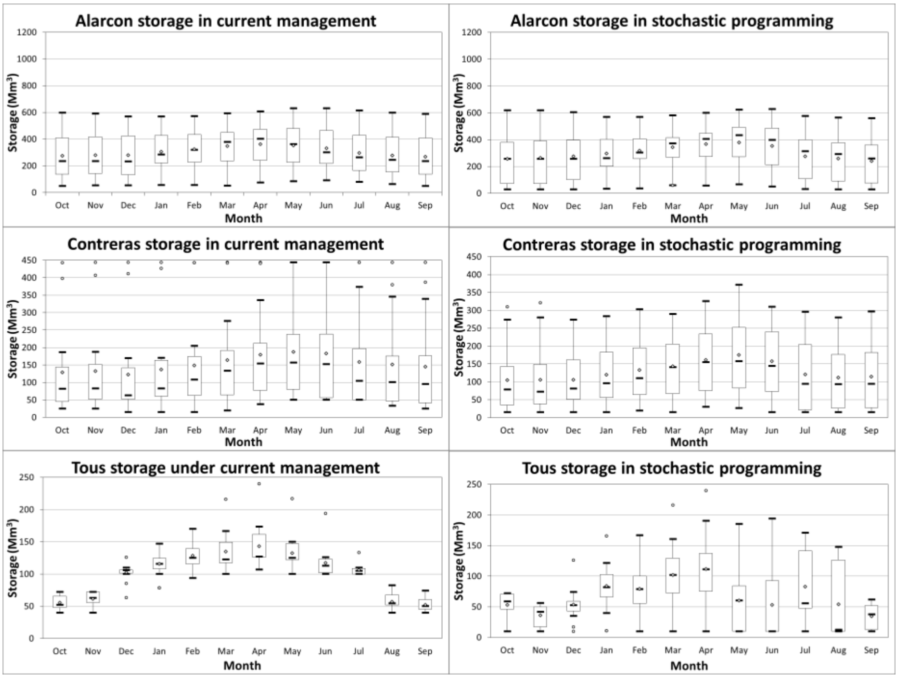


Fig. 6.4: Box-whisker plots of monthly storages in the main Jucar river basin reservoirs

In the Contreras reservoir, the stochastic optimization results present both carryover and seasonal storage, as seen in the wideness of the box-whisker plots, the smooth refill-drawdown cycle and the lack of summer outliers. On the other hand, the current operation show a non-negligible in-year operation, especially between October and April, in which the box-whisker plots are narrower than in the stochastic programming. Nonetheless, no significant differences between alternatives are found.

The results of Tous, downstream Alarcon and Contreras and with smaller capacity, offer remarkable differences between alternatives. The current management reproduces a steady refill-drawdown cycle, as noticed by the narrow box-whisker plots. This cycle is in line with the irrigation season, refilling it from October to April and emptying it from May to September. This steady behavior is absent from the stochastic optimization results, as seen in the wider box-whisker plots. Furthermore, stochastic programming drawdowns Tous differently from the current operation, given the storages found between May and September. It lowers Tous in May and June, increases the storage a little in July and then drawdowns it again until the end of the irrigation season. This is in line with the use of Tous as the tail reservoir of the hydropower system, since energy prices in July are higher than in the neighboring months, so the system increases the hydropower production and stores the turbined water in Tous.

On a broader view, differences between the current management and stochastic programming focus on Tous. The current operation implements similar refill-drawdown strategies regardless of the year. In a distinct way, stochastic optimization adapts Tous operation to the hydrological variations, as noticed in the wider box-whisker plots in comparison with the current management. This is consistent with the algorithm construction, which considers inflow forecasts. Furthermore, it increases turbined flows and stores them in Tous, in contrast with the current practices. Using Tous as the tail reservoir of the hydropower system, increasing carryover storage in Contreras employing dynamic inflow forecasts are the main differences between the current operation and the stochastic optimization.

6.4.3. Conjunctive use operation

The monthly allocations to the demands that have groundwater as their main source (Mancha Oriental agricultural demand, MOAD; and canal Jucar-Turia, CJT) have been contrasted to determine the conjunctive use operations implemented by both alternatives (Fig. 6.5). Differences are larger during summer than during winter, since it is the period in which the irrigation demands concentrate. As appearing in the MOAD scatterplots, the stochastic optimization decreases groundwater abstractions. This is caused by the consideration of the stream-aquifer interaction between the Mancha Oriental aquifer and the Jucar river.

Stochastic optimization balances the marginal benefits of allocating water to the MOAD with the marginal supply costs plus the opportunity costs of increasing downstream flows due to stream-aquifer interaction. In contrast, the current operation does not consider the opportunity costs associated with the stream-aquifer interaction, leading to higher (and less efficient at the systemwide scale) pumping rates. The average decrease offered by stochastic optimization is steady across the year, reducing pumping by 24% compared to the current operation. The increase in surface deliveries by stochastic programming is also steady, equal to 179% of the current situation, although far from the decrease in pumping rates.

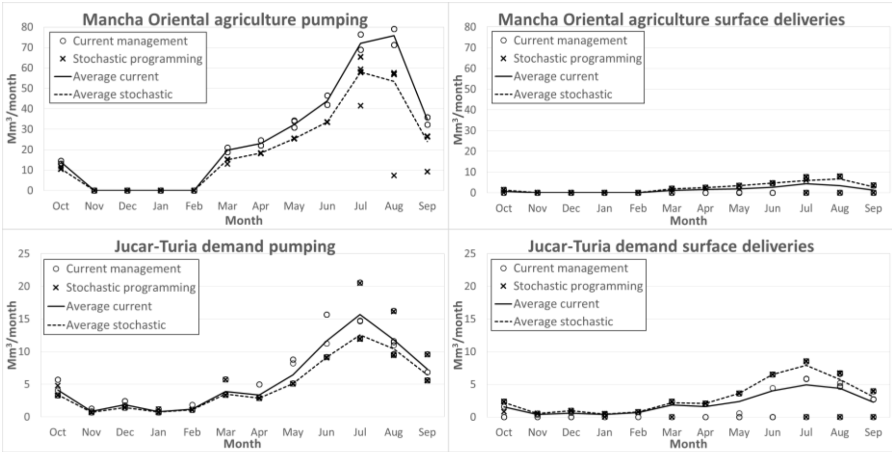


Fig. 6.5: Scatterplots of monthly deliveries to Mancha Oriental and Jucar-Turia demands

The scatterplots corresponding to the CJT demand show a different behavior. In them, stochastic optimization allocates a slightly higher amount of water resources and reduces pumping by the same quantity. The sum of both sources of supply is similar regardless of the alternative (see Table 6.1), which is consistent with the absence of stream-aquifer interaction. Since there are no significant systemwide opportunity costs, both alternatives balance the marginal benefits of supply with the marginal pumping costs. Differences between them are caused by the fact that stochastic optimization is able to allocate more surface water resources due to the improved management achieved in the rest of the basin. The results of the stochastic programming show a 15% decrease in the pumping amount, which is almost entirely replaced by surface resources.

6.4.4. Discussion and conclusions

The management decisions adopted by stochastic programming offer an average increase of 1% (5.29 M€/year) in the systemwide benefits. It grows to 1.7% (8.52 M€/year) during the drought period experienced between 2005 and 2008. The reason why this rise in revenues is limited in percentage is the efficiency possessed by the current operating rules, which are product of a long-term experience. Nevertheless, the stochastic programming is able to allocate water in a more economically-efficient way. The following conclusions regarding the method and its application can be drawn:

- The CSG-SDDP extended algorithm, combining the Stochastic Dual Dynamic Programming algorithm and the Embedded Multireservoir Model, has been successfully applied. It is able to account for stream-aquifer interactions in the definition of optimal operating decisions.
- Its application to the Jucar river system has been capable of outlining changes in the operation of reservoirs and aquifers, taking advantage of a joint management of them. The CSG-SDDP is able to define optimal conjunctive-use strategies in large-scale water resource systems using stochastic programming.

The main changes identified by the CSG-SDDP algorithm in the Jucar river system operation have been:

- Reduce groundwater abstractions from the Mancha Oriental aquifer around 80 Mm^3/year (responsible of most of the improvement).
- Increase carryover storage in Contreras (although not significant).
- Use Tous as the tail reservoir of the hydropower system.
- Make a joint management of the reservoirs and the Mancha Oriental aquifer during droughts, curtailing surface and groundwater allocations simultaneously.

The pumping reduction proposed is in line with the policy objectives set by the River Basin Authority on the Mancha Oriental aquifer (CHJ, 2013), whose goal is to reduce its overexploitation. However, the main reason invoked by the CHJ is the recovery of the Mancha Oriental aquifer levels due to environmental reasons. The fact that the CSG-SDDP model, without environmental constraints on the Mancha Oriental levels, arrived to a similar conclusion, means that recovering the aquifer is not only desirable due to environmental reasons, but may also be economically efficient in comparison with the *statu quo*.

The CSG-SDDP was successfully applied to the Jucar river system due to the existence of adequate data to fit the EMMs. The development of an EMM would require assessing the natural stream-aquifer interaction, as well as the current one, using the principle of superposition if possible. The estimation of both needs adequate streamflow records, recharge and pumping measurements and groundwater modeling techniques able to isolate the natural and the anthropic components. These premises limit the applicability of the CSG-SDDP to systems in which an EMM could be adequately fitted and the natural regimen could be reasonably estimated. The algorithm is also subject to the SDDP method requirements, including the necessity of convex benefit-to-go functions. To be applicable, the CSG-SDDP needs to fulfill both the requirements of the SDDP and the EMM algorithms.

Regarding the computational power needs of the algorithm, each EMM increases the dimensionality of the CSG-SDDP as increasing the number of reservoirs by one for a SDDP algorithm, as found in tests done with ESPAT_R and ESPAT_RA. However, the need of computing power is far from being a serious issue. The CSG-SDDP implementation in GAMS (ESPAT_RA), solving each one-stage optimization problem with nonlinear programming (CONOPT3 solver), spent 1 hour and 22 minutes to solve the Jucar river system model previously described in an Intel Core2 Quad CPU with 6.00 GB RAM. A deterministic variant of the same problem, solved using ESPAT_DET with nonlinear programming (CONOPT3 solver), took 31 minutes. The CSG-SDDP model implementation in GAMS benefits from the Gather-User-Solver-Scatter (GUSS) procedure (Bussieck et al., 2011), which distinctly reduces the time needs.

Moreover, the mathematical representation of the system is subject to several uncertainties. The demand functions/curves and the economic characterization of energy production are the most important as they drive the allocation decisions. Further research would be advisable in order to improve the economic characterization of the system while keeping a good representation of the global picture, which is decisive for systemwide-focused models. Considering the remaining sources of uncertainty, the parameters and mathematical representations assumed by the model are the same as used by the CHJ (CHJ, 2013), whose river basin mathematical models are product of a continuous development, testing and update process started many years ago.

It should also be remarked that, although the EMM has been found able to efficiently reproduce complex stream-aquifer interactions in water resource management models at the systemwide scale, for a wide range of aquifer behavior including karstic aquifers (Andreu et al., 1996; Estrela and

Sahuquillo, 1997; Pulido-Velazquez et al., 2008, 2006a, 2005; Sahuquillo, 1983), it does not reproduce groundwater heads. Consequently, the operational changes obtained by an EMM (such as reduce pumping) should be further downscaled to the groundwater body scale by groundwater models such as finite-difference ones. Although some complex groundwater modeling methods, such as the eigenvalue method (Sahuquillo, 1983), are compatible with systemwide optimization models (Andreu et al., 1996; Pulido-Velazquez et al., 2006a), they have been so far applied to deterministic optimization approaches, and its extension to stochastic equivalents is a matter of further research.

Furthermore, optimization has been done following the common social-planner paradigm, in which the goal is set on maximizing the systemwide net benefits. However, the resulting allocation strategy would imply an asymmetrical distribution of revenues causing equity issues. To deal with them, cooperation strategies should be explored using, for example, Game Theory (Madani, 2010; Madani et al., 2014; Madani and Hipel, 2011), and solved applying proper benefit-sharing mechanisms (Arjoon et al., 2016).

In spite of the slight improvement of the economic results achieved by the CSG-SDDP in the Jucar river system, the application can be considered as successful, given its capacity to suggest operation changes and the consideration of stream-aquifer interactions. It is likely that the application of the algorithm to other basins would lead to more significant increases in revenues.

7. APPLICATION 2: DSS TOOL FOR THE JUCAR RIVER SEASONAL OPERATION[4]

The conjunctive use model successfully outlined several operational changes able to improve the efficiency of the Jucar river system management. However, the changes affecting the way the reservoirs are balanced need to be contrasted with the current decision-making processes of the Jucar River Basin Authority (CHJ) Operation Office and Reservoir Releases Commission. This comparison is crucial in order to frame the prospected improvements within the current practices.

The optimization results provided by stochastic programming should therefore be merged with the current decision-making processes at the seasonal scale. Expert knowledge is explicitly required in the reproduction of these procedures and in the setup of models and tools able to match the goals, criteria, constraints and traditions they take into account. This chapter presents the application of the collaborative framework to combine expert knowledge and optimization results outlined in chapter 4 to the definition of a DSS tool for the seasonal management of the Jucar river.

The purpose of this application is to improve the seasonal operation of the Jucar river system. The monthly time scale is chosen for the simulation models developed. Considering the fact that the Jucar river is subject to multiannual droughts whose whole extension should be included in the analysis period, a time horizon of ten years has been defined for these models. Nonetheless, the time scale and time horizon of the DSS tool created to support the seasonal decision-making has been defined following the desires and needs of the system operators.

[4] The application described in this Chapter is partially presented in Macian-Sorribes and Pulido-Velazquez (2017). Its use in this thesis complies with the Copyright Transfer Agreement signed between the authors and the American Society of Civil Engineers (ASCE)

7.1. DSS TOOL FOR THE JUCAR SYSTEM

To support and further improve the seasonal operation of the Jucar river system, it is necessary to build a Decision Support System (DSS) mimicking the current decision-making processes. Particularly, it should estimate how much water should be allocated to the agricultural users during the irrigation season (May-September) and how much should be released from each of the main reservoirs (Alarcon, Contreras and Tous) to guarantee the planned deliveries. These decisions are currently taken on the basis of expert knowledge, without the aid of a formal DSS. This lack implies that the operating rules followed are not explicitly stated, hampering the analysis of the system response to different inflow scenarios (expert knowledge is required to study the implications of each alternative). Under these circumstances, a DSS would enable the analysis of more likely scenarios in an easier way. It would also provide an explicit mathematical representation of the operating rules, and therefore collect and preserve the expert knowledge used in their definition. The stages presented in chapter 4 have been used.

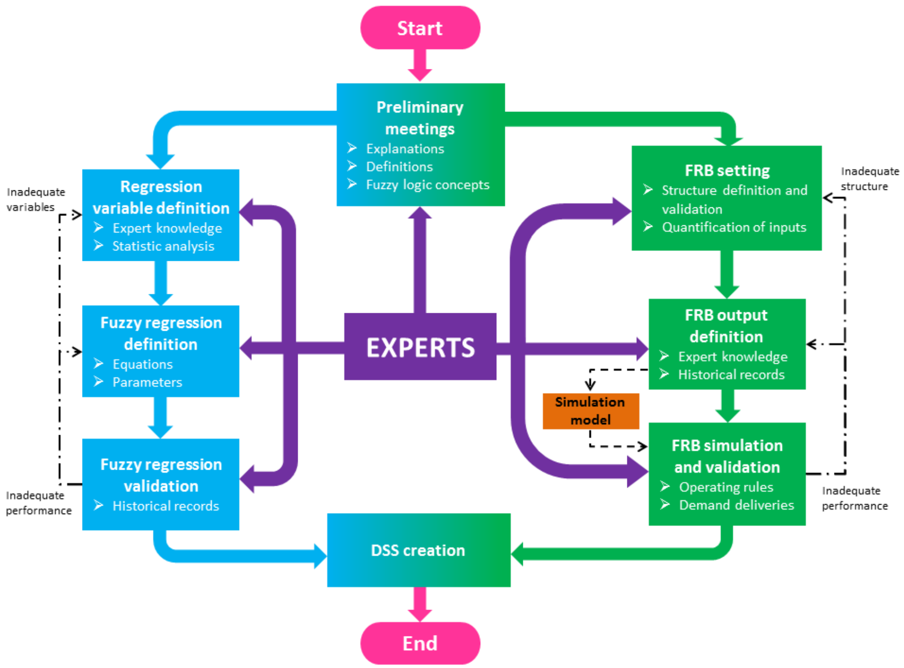


Fig. 7.1: Framework for improving decision-making in the Jucar river

7.1.1. Previous meetings and model co-development

The main goal of the preliminary meetings with the system operators (the experts) was to obtain a clear picture of how the Jucar river system is seasonally managed, to clarify the terms used in the process (avoiding potential misunderstandings), and to introduce fuzzy logic to them. These meetings have been decisive in creating confidence between researchers and system operators. The general *modus operandi* of the system has been described in subsection 5.2.2.

Before the irrigation season, the CHJ Operation Office predicts inflows using a deterministic forecast method based on past observed inflows, precipitation projections for the irrigation season, past rainfall observations, 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 storages 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 features explained by the system operators, a Jucar river seasonal operation model has been defined, incorporating the input and decision variables the CHJ Operation Office uses in its seasonal decision-making (Fig. 7.2, features presented in Appendix A3.1). Storage in the main reservoirs of the system (Alarcon, Contreras and Tous) and the inflow from the four sub-basins they consider (Alarcon, Contreras, middle and lower) are the input variables of the Jucar river seasonal operation. The inflows for the historical period have been calculated by water balances as done by the Operation Office.

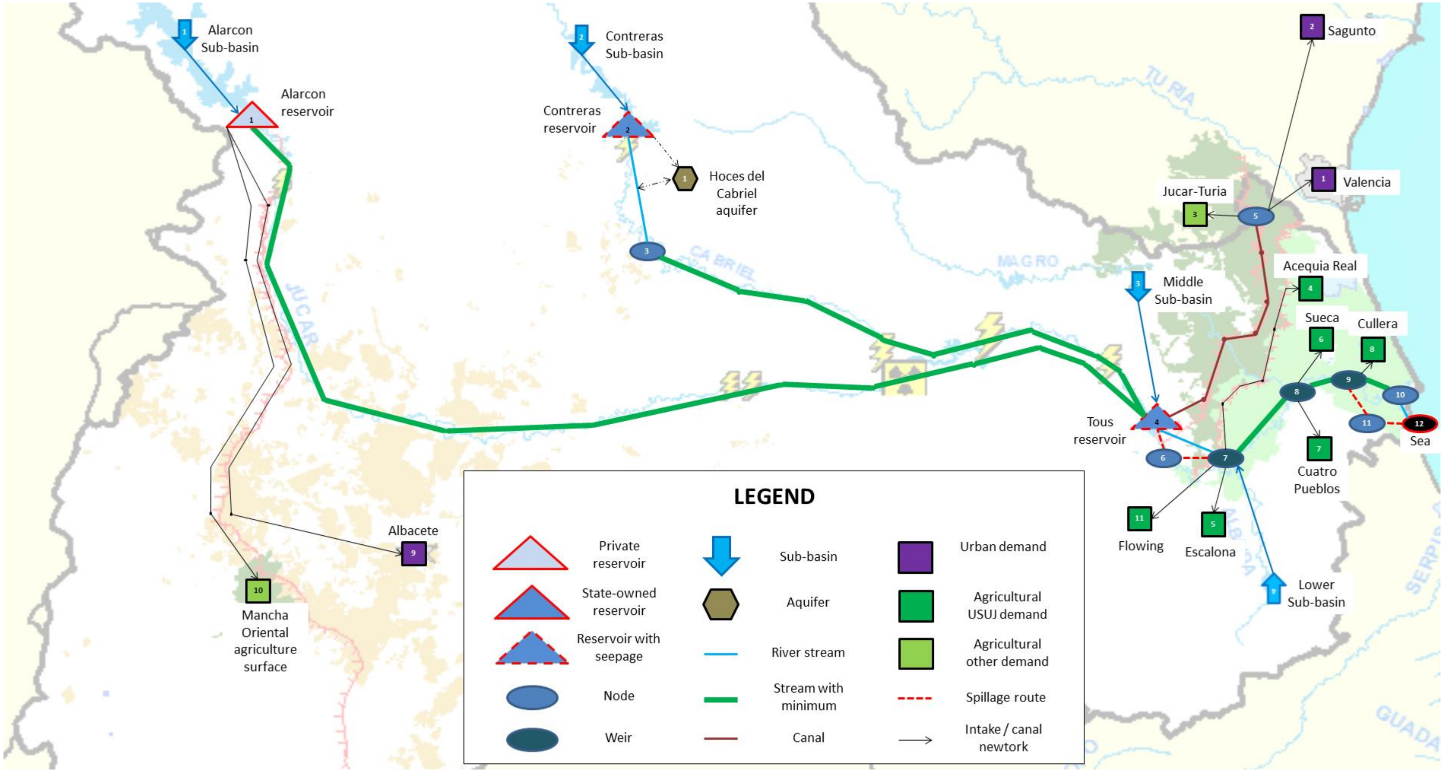


Fig. 7.2: Jucar river seasonal operation model network flow

Three urban demands and eleven irrigation demands are included, in accordance with the demand division considered in the seasonal decision-making of the system. Groundwater pumping rates allowed are not decided by the Operation Office, so groundwater demands have not been included and mixed demands have been curtailed to the maximum surface amount they are entitled to. For the same reason, groundwater bodies have not been modeled. The influential stream-aquifer interaction between the Mancha Oriental and the Jucar river is already implicit in the middle sub-basin inflow time series. The only aquifer explicitly modeled is Hoces del Cabriel, and it has been included exclusively to mathematically represent the return of the Contreras seepage losses to the Cabriel river (CHJ, 2013).

Deliveries to the Cofrentes Nuclear Power Plant must be fully guaranteed and, consequently, they have been treated as a constraint by subtracting the net amount of water consumed from the middle sub-basin inflow time series. Hydropower plants are not considered as their schedule is made by the power companies, not the CHJ Operation Office, being restricted to not turbine more water than the one allocated to the downstream consumptive uses (see subsection 5.2.2). The environmental flows included in the model are the ones that directly constrain the seasonal management: the minimum releases from Alarcon and Contreras and the outflows to the sea. Additionally, some links have been added to the model to measure undesired spills from Tous and sea outflows higher than planned, as minimizing them is one of the goals of the Jucar seasonal management.

7.1.2. FRB setting: delivery and release FRB systems

In the Jucar river system, the decision-making process involves two main stages. At first, the Reservoir Releases Commission decides how much water should be delivered to the users during the upcoming season (May-September). After this, the system operators (Operation Office) decide how to balance the releases/storages from the different reservoirs to meet the scheduled deliveries, based on their initial state and the forecasted inflows. The period corresponding to the irrigation season (from May to September) is taken as a single time step in this decision-making.

Accordingly, two fuzzy-rule based (FRB) systems were built and linked to reproduce the current decision-making processes (Fig. 7.3). The delivery FRB reproduces the decisions made by the Reservoir Releases Commission, establishing the amount of water to release from Tous based on the joint system storage (Alarcon, Contreras and Tous) and the lower sub-basin inflows. The amount of water available for the downstream agricultural users is the release from Tous plus these inflows. The release FRB represents the decisions 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, to guarantee the deliveries scheduled by the Reservoir Releases Commission, considering the storages and the forecasted inflows from the middle sub-basin.

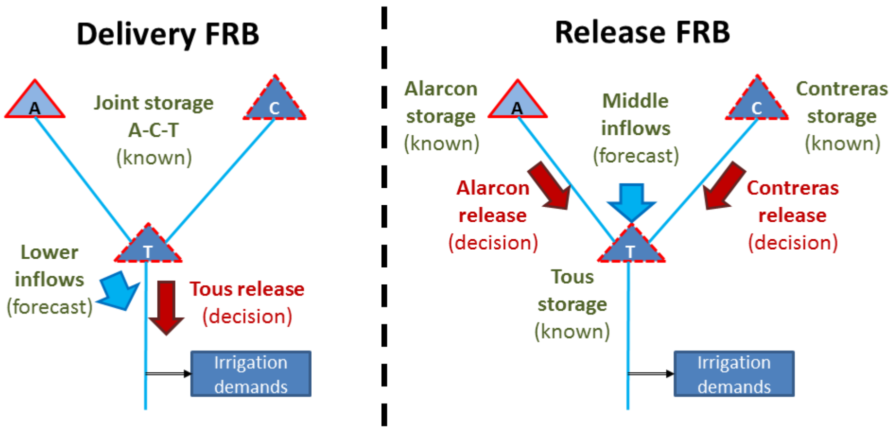


Fig. 7.3: Jucar river operating rules representation with FRB systems

Regarding the deliveries to Albacete and the Mancha Oriental, the first is always met (it is an urban demand). The second is entitled to 33 Mm^3 per irrigation season from Alarcon, which is supplied if the Alarcon Agreement allows it. So, both demands are not considered by the FRB systems.

The 2 inputs of the delivery FRB (joint storage and lower sub-basin inflows) have been characterized using 5 fuzzy numbers (Fig. 7.4), leading to 25 fuzzy rules (5·5). The output of this FRB (release from Tous) has been characterized as a non-fuzzy number (value in Mm^3), whose values are defined combining expert knowledge, historical records and optimization results. The membership functions of the fuzzy numbers have been estimated using the vertical method considering two *α cuts* associated with the degrees of membership 0 and 1 (subsection 2.2.3). A workshop with the system operators was organized in order to agree with them on the input quantification. They 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.

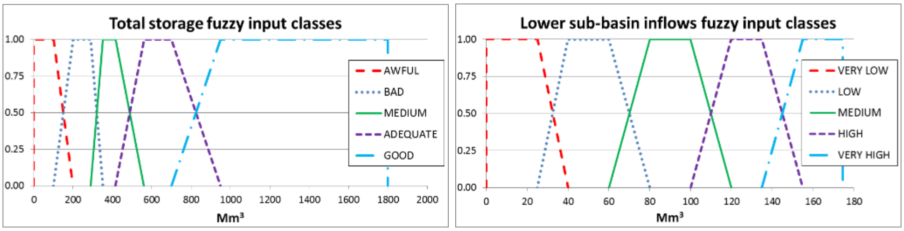


Fig. 7.4: Fuzzy inputs for the delivery FRB

The 4 inputs of the release FRB (storage at each reservoir and middle sub-basin inflows) have been characterized using 3 fuzzy numbers (Fig. 7.5), combining together to 81 fuzzy rules (3·3·3·3). The 2 outputs of this FRB (releases from Alarcon and Contreras) have been defined as non-fuzzy numbers (percentage with respect to Tous), whose values are defined in a similar way than the delivery FRB. The membership functions of the fuzzy numbers have been estimated, using the same vertical method as for the delivery FRB, within the same workshop organized with them. Both the inputs and the outputs refer to the whole irrigation season (from May to September), so the decisions obtained from the FRB systems need to be further downscaled by establishing a release calendar. This downscaling is defined, implemented, and supervised by the Operation Office.

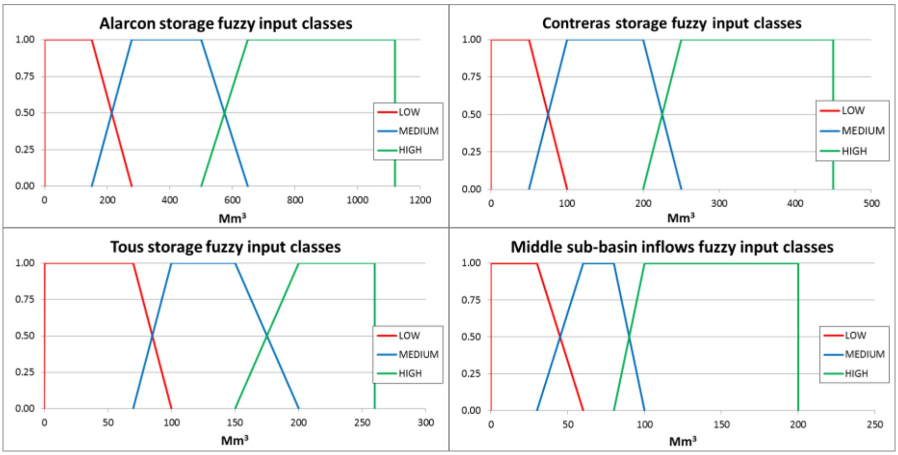


Fig. 7.5: Fuzzy inputs for the release FRB

7.1.3. FRB outputs for the current operation

Regarding the delivery FRB, historical records from the 2003-2013 period were used to quantify the output values. They were employed as the main information source since the decision reproduced by the delivery FRB corresponds to the one made by the Reservoir Releases Commission, from which enough members could not be approached. A variant of the weighted-counting algorithm was employed in the quantification process (Shrestha et al., 1996). The rules whose outputs could not be determined by historical data (because they were never triggered during the historical period) were given a value based on the expert knowledge from the system operators of the Operation Office.

For the release FRB, the outputs were defined on the basis of the expert knowledge transmitted by the system operators from the Operation Office. In a workshop, they were given a set of possible management situations (corresponding to different combinations of storages at the beginning of May and forecasted inflows between May and September) and asked about the decision they would have made under these circumstances. The answers obtained were used to derive the outputs of the release FRB.

The delivery and release FRB systems obtained have been validated against the historical records available. This stage has been done with the aid of the Jucar river seasonal operation model, which has been introduced in the STIG_FRB tool. Since the model works at the monthly scale while the FRB systems consider the irrigation season as a whole, it has been necessary to downscale them and to define an operation scheme applicable out of the irrigation season.

Given that the agricultural demands out of the irrigation season are low, the system operating rules between October and April have been approximated by fixing a release ratio between Alarcon and Contreras (43%/57%) based on the historical time series, while guaranteeing enough joint releases to satisfy the urban demands and the environmental flows.

The downscaling of the FRB systems' results to the monthly scale has been done with the following operations:

- A coefficient has been established as the division between the target release from Tous obtained by the delivery FRB and the total downstream demand during the irrigation season.
- A monthly limit to the Tous releases has been established as the previous coefficient times the total downstream demand for the given month.
- Alarcon and Contreras releases have been restricted to the percentage of Tous obtained from the release FRB, being kept the same during the whole irrigation season. This restriction is modeled as a soft constraint, so small violations are allowed to guarantee the releases from Tous.

In the absence of the inflow forecasts employed by the Operation Office during the historical period, the inflow values introduced to the FRB systems were the historical ones. This means that the FRB systems worked under perfect forecast conditions during the validation stage. This is consistent with the historical records, with represent the *ex post* situation.

The historical records used in the validation stage span between 2003 and 2012. They consist of storages and releases in the three reservoirs facilitated by the CHJ Operation Office, streamflow time series in several locations obtained from CEDEX (2013), and demand deliveries recorded by the CHJ Operation Office. The validation results appear in Appendix A3. Validation has been successful, especially in reproducing the reservoir levels and the demand deliveries, so the FRB structure defined, and the outputs quantified using expert knowledge and historical records, offer a proper representation of the current decision-making processes and the current seasonal operation of the Jucar river system.

7.1.4. Seasonal inflow forecasting in the Jucar river system

In order to build a DSS able to make *ex ante* projections of release decisions, it is necessary to determine a mechanism to forecast inflows for the upcoming irrigation season. For this purpose, an inflow forecasting procedure has been developed for the Jucar river system based on fuzzy regression (see subsection 2.2.2). A fuzzy linear regression equation was fitted for each sub-basin in order to forecast the future seasonal inflow based on past meteorological and hydrological variables. The procedure is able to accommodate the system operators' choice of independent variables, it is conceptually simple and offers a way to estimate the imprecision associated with the regression process by using fuzzy numbers as outputs. Furthermore, it can provide suitable results even when available data records are scarce.

Regression variables

To set up the regression equations for each sub-basin, the system operators pointed out different variables they consider when making inflow forecasts for the next irrigation season, as rainfall and inflows in the past months (up to 2 years in advance). For the given candidate variables, a statistical correlation analysis between them and the inflows during the irrigation season was used to rank them and choose the final input variable set (Table 7.1). Not all the candidate variables could be used because observations cover just 10 irrigation seasons, so it is advisable to reduce its number as much as possible.

Table 7.1: Correlation analysis for inflow forecasting in the Jucar river

Variable	Sub-basin	Inflows May- September				Variable	Sub-basin	Inflows May- September			
		Alarcon	Contreras	Middle	Lower			Alarcon	Contreras	Middle	Lower
Rainfall in past Oct-April	Alarcon	0.68	-	-	-	Rainfall past 12 months	Alarcon	0.68	-	-	-
	Contreras	-	0.85	-	-		Contreras	-	0.70	-	-
	Middle	-	-	0.60	-		Middle	-	-	0.49	-
	Lower	-	-	-	0.53		Lower	-	-	-	0.48
Rainfall past 18 months	Alarcon	0.72	-	-	-	Rainfall past 24 months	Alarcon	-0.12	-	-	-
	Contreras	-	0.65	-	-		Contreras	-	-0.03	-	-
	Middle	-	-	0.50	-		Middle	-	-	0.09	-
	Lower	-	-	-	0.38		Lower	-	-	-	0.13
Inflows in past Oct-April	Alarcon	0.69	-	-	-	Inflows in past April	Alarcon	0.65	-	-	-
	Contreras	-	0.87	-	-		Contreras	-	0.89	-	-
	Middle	-	-	0.80	-		Middle	-	-	0.87	-
	Lower	-	-	-	0.49		Lower	-	-	-	0.47

Given the correlation coefficients obtained, the following variable selection has been made, in which two explanatory variables have been used except for the lower sub-basin, whose low correlation coefficients forced the definition of three explanatory variables:

- Alarcon sub-basin: rainfall from previous October to April, and inflow in the same period.

- Contreras sub-basin: the same as Alarcon.
- Middle sub-basin: rainfall from previous October to April and inflow in the previous month (April)
- Lower sub-basin: rainfall from previous October to April, inflow during the same period and inflow in previous April.

For the same data scarcity reasons, spatial cross-correlations between sub-basins have not been considered. Correlation coefficients are higher in the upper sub-basins, decreasing when moving downstream.

Regression fitting and validation

The fuzzy coefficients of the regression were fitted for the first 8 years of observations (2003-2010), being left the last 2 for validation (2011-2012). The membership threshold value (*h*) was set at 0.25, as higher values would enlarge too much the width of the fuzzy coefficients and the fuzzy outputs. The resulting equations have been:

Alarcon: $$\tilde{q} = [0.04; 0.08; 0.20] \cdot P_{O\ to\ A} + [0.02; 0.17; 0.28] \cdot q_{O\ to\ A}$$

Contreras: $$\tilde{q} = [0.01; 0.14; 0.20] \cdot P_{O\ to\ A} + [0.01; 0.12; 0.22] \cdot q_{O\ to\ A}$$

Middle: $$\tilde{q} = [0; 0.08; 0.09] \cdot P_{O\ to\ A} + [0.18; 1.83; 3.34] \cdot q_{A}$$

Lower: $$\tilde{q} = [0.02; 0.12; 0.22] \cdot P_{O\ to\ A} + [0.11; 0.25; 0.46] \cdot q_{O\ to\ A} + [0.01; 0.50; 0.65] \cdot q_{A}$$

Where *q* inflows; *P* rainfall; *O* October and *A* April. The triangular fuzzy numbers have been represented using the notation [lower support, modal value, upper support].

The results obtained with the fitted equations for the 10 years are shown in Fig. 7.6, in which the historical records (red circular markers joined by red dashed lines) are shown against the fuzzy predictions (modal values in green fill lines and membership functions approximated through blue-shaded areas, the darker the higher the membership degree). As expected, the vagueness (area covered by the blue shade tones) is higher in the regressions of the sub-basins with lower correlation coefficients. In any case, most observations fall in the region of non-pale blue tones, so the adjustment is acceptable considering the scarce data available.

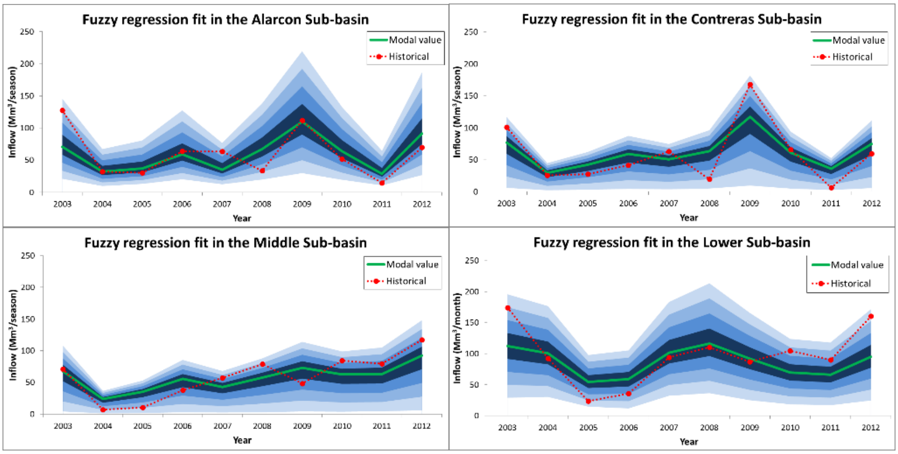


Fig. 7.6: Fuzzy linear regression results for the Jucar river basin

7.1.5. FRB outputs based on stochastic programming

The stochastic optimization model to be merged with expert knowledge has been built using the CSG-SDDP algorithm and the ESPAT tool. The system representation adopted is the same as the seasonal operation model (Fig. 7.2), including the specific constraints. The objective function is the maximization of the weighted sum of the current deliveries plus the future expected ones, in which the weights are the priorities given to the demands for each month (see Appendix A3).

The optimization model has been run, using the CSG-SDDP implemented in ESPAT_RA, for a 10-year period, at the monthly scale, considering 20 openings in the backward optimization and 20 time series in the forward simulation, including the historical inflows. After its execution, the optimal storages, flows and deliveries were post-processed to be used in modifying the delivery FRB and the release FRB.

The determination of the FRB outputs corresponding to an optimal operation of the system has been made using the results obtained from the optimization algorithm for the 20 inflow time series. These results have been upscaled from the monthly to the irrigation season scale:

- For each irrigation season, the initial storages have been defined as the ones at the end of April for the corresponding hydrological year.
- The inflows from the middle and lower sub-basins for each irrigation season have been defined as the summation of all the inflow values between May and September for the given hydrological year.
- The same procedure as for the inflows has been followed to obtain the irrigation-period releases.

Consequently, the resulting 10-year 20 time series represent 200 irrigation season results. Using them, the same weighted-counting algorithm as employed before (Shrestha et al., 1996) has been used to estimate the outputs of both FRB systems. Out of the irrigation season, the same operating rules as under the current management have been used.

Only the outputs of the FRB systems have been modified by the stochastic programming algorithms. Using the same FRB structure for both the current and the optimization-based rules guarantees that the decision-making processes are reproduced in the same way, as the only difference between them is the decision made. This close reproduction of the current decision-making processes is crucial in making the optimization-based operation applicable to real-life operational decisions.

7.2. DSS TOOL AND RESULTS

The FRB systems and the validated fuzzy regression equations have been combined into a DSS tool able to make *ex ante* projections of future inflows, likely management decisions and their consequences. Depending on the operating rules reproduced by the FRB systems (either the current or the optimal), the DSS tool would work considering the current operation of the Jucar river system or an optimal management.

7.2.1. DSS tool reproducing current decision-making

To be able to use the fuzzy inflow forecasts as inputs of the FRB systems, the latter have been adapted to work with fuzzy inputs. The fuzzy input composition scheme presented in Jones et al. (2009) has been used. It consists in:

1. Decomposing each fuzzy input into a set of non-fuzzy inputs, each one corresponding to certain membership degree.
2. Using the non-fuzzy inputs previously obtained for the same membership degree (which in practice correspond to the limits of the α-cuts of the fuzzy inputs) in a standard fuzzy inference process in which non-fuzzy outputs are obtained. Each non-fuzzy output set should be attached the corresponding membership degree.
3. Repeating the process for all the membership degrees in which the fuzzy inputs were decomposed.
4. Build the fuzzy outputs using the non-fuzzy outputs obtained and the membership degree attached to each of them.

After computing the fuzzy outputs, their consequences (water availability and end-of-season storages) have been calculated by performing fuzzy water balances using fuzzy arithmetic (e.g. Simonovic, 2009). In particular, the following equations were used:

Alarcon storage: $\widetilde{E_A} = S_A + \widetilde{I_A} - \widetilde{R_A}$

Contreras storage: $\widetilde{E_C} = S_C + \widetilde{I_C} - \widetilde{R_C}$

Tous storage: $\widetilde{E_T} = S_T + \widetilde{I_M} + \widetilde{R_a} + \widetilde{R_C} - \widetilde{R_T}$

Water availability: $\widetilde{W} = \widetilde{R_T} + \widetilde{I_L}$

Where S_A, S_C and S_T storages at the start of the irrigation season in Alarcon, Contreras and Tous; $\widetilde{E_A}$, $\widetilde{E_C}$ and $\widetilde{E_T}$ storages at the end of the season; $\widetilde{R_A}$, $\widetilde{R_C}$ and $\widetilde{R_T}$ releases during the season; and $\widetilde{I_A}$, $\widetilde{I_C}$, $\widetilde{I_M}$ and $\widetilde{I_L}$ inflows during the season from the Alarcon, Contreras, middle and lower sub-basins. The DSS has been divided into two 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. These tools have been named as the predictive and the decision-making tool.

Predictive tool

The predictive tool (Fig. 7.7) makes projections on likely decisions that could be made in response to the current system state, and the corresponding consequences.

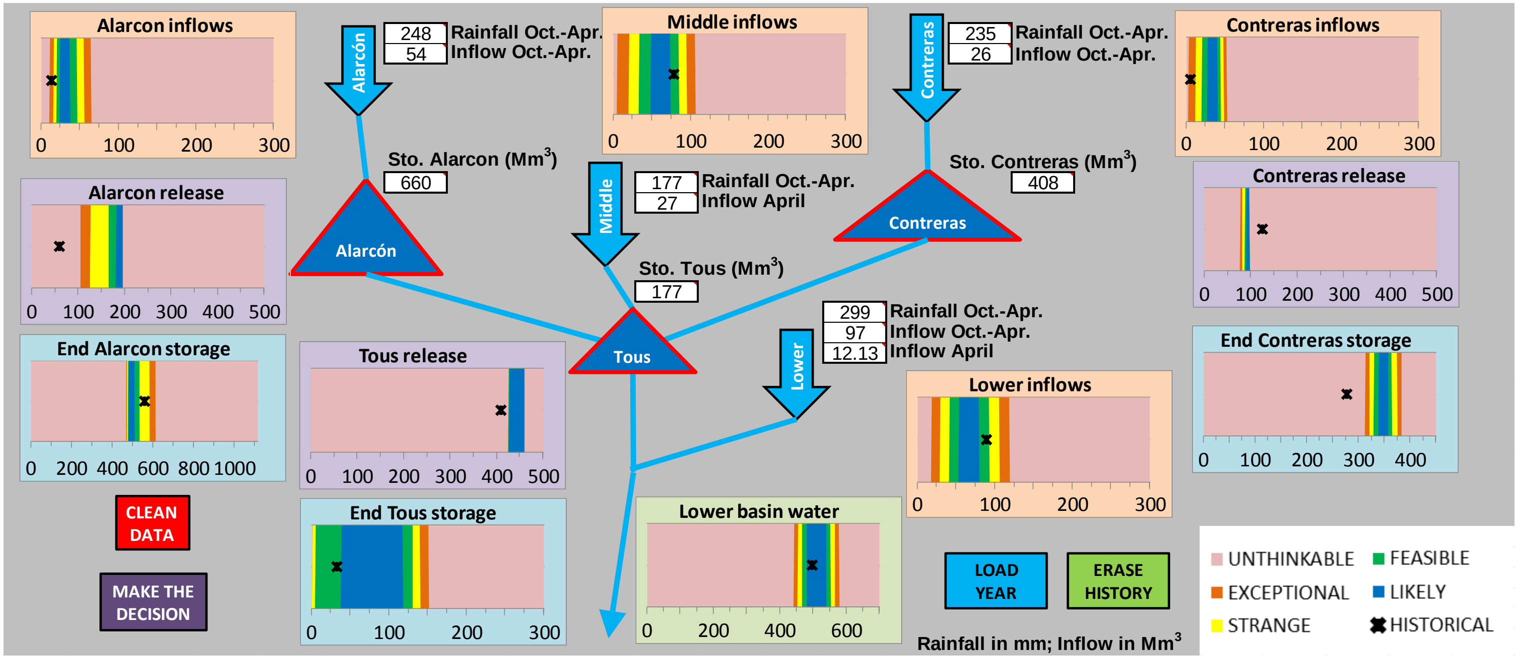


Fig. 7.7: DSS predictive tool for the Jucar river system

Instead of making a single choice, it forecasts how the system would look like in response to the initial system state, the inflows projected and any likely decision that would be made regarding them. Therefore, the user has a quick view of any likely operating decision to be taken in May (amount of water to release between May and September), as well as the prospected system state at the end of September and how much water would be delivered to the downstream users during the whole irrigation season.

For the application of the predictive tool, the user has to introduce the information required to make the future state projections (white cells), and then checking the predicted values of the system state variables in response to them (graphs). The information required corresponds to the meteorological and hydrological variables needed to make inflow projections (past rainfall and discharges), and the initial system state (reservoir storages at the beginning of the irrigation season).

The fuzzy future inflows (salmon graphs) are obtained using the fuzzy regression equations shown in subsection 7.1.4, for which the meteorological and hydrological inputs are required. The fuzzy release decisions (violet graphs) are obtained through performing a fuzzy inference procedure with fuzzy inputs (the fuzzy inflow projections) on the FRB systems representing the current operating rules. For this, initial storages in the three reservoirs are required. The fuzzy end-of-period storages (pale blue graphs) are calculated using fuzzy arithmetic employing the fuzzy inflow projections, the fuzzy releases prospected by the FRB systems and the initial storage values. Water availability and consequences are computed using fuzzy arithmetic, requiring the fuzzy releases from Tous and the fuzzy inflows forecasted for the Lower sub-basin.

To ease the interpretation of the fuzzy numbers appearing in the predictive tool, a color code attached to linguistic descriptors has been employed, associated with the membership degrees (μ) of the fuzzy numbers, as follows:

- *Unthinkable* (pale red, $\mu = 0$): *ex ante* decisions within this area should not be taken into account, since they will be fully inconsistent with the current operating rules.

- *Exceptional* (orange, $0 < \mu \leq 0.25$): *ex ante* decisions within this zone would be inconsistent with the operating rules, although they may be acceptable under extreme situations not found in the last years.
- *Strange* (yellow, $0.25 < \mu \leq 0.50$): *ex ante* decisions in this area may be acceptable only if proper reasons support them.
- *Feasible* (green, $0.50 < \mu \leq 0.75$): any *ex ante* decision falling within this area would be consistent with the operating rules and the inflow expectations.
- *Likely* (blue, $0.75 < \mu$): ex ante decisions inside of this zone would be the most acceptable ones, being fully consistent with the inflow expectations and the operating rules.

The color codes are the primary metric for comparing release decisions, locating and sorting operation options by their likelihood. Any *ex ante* decision falling within the *feasible* or the *likely* zones would be in line with the expected inflows and the current operating rules. Decisions inside the *exceptional* and *strange* areas would require additional information in order to determine if they are suitable or not. Decisions falling in the *unthinkable* zone should not be considered at all.

Therefore, the user has an immediate estimation of which decisions are the most promising. The visual setup of the tool and the use of linguistic descriptors facilitates the understanding and comparison of the decisions. The tool screens all possible values of the different variables, so any management alternative is explored regardless of its suitability. The simultaneous estimation of the end-of-period system state and the water availability allows any user to determine if discretional decisions (like adopting releases not in line with the current rules, or allow pumping in the downstream demands) would be required prior to making the final release decision.

For example, if water availability for the downstream demands shows low values for both the *feasible* and *likely* intervals, then a discretional decision is required. It would consist in increasing the release from Tous, which would imply higher releases from Alarcon and Contreras, or in allowing pumping to complement the surface deliveries. Similarly, if Tous presents lower storages than desired, more water should be released from Alarcon and Contreras than the one in line with the current operating schemes, and the other way round if Tous storage is higher than desired.

Despite ranking any possible decision and offering a global picture of the system, the predictive tool does not pick a single option as the best. Making a precise decision would oppose the spirit of the tool, which is supposed to *support*, not *replace*. For this, it provides a set of promising alternatives, which can be used as a starting point for negotiation processes between users and decision-makers.

Decision-making tool

The decision-making tool (Fig. 7.8) aims at estimating the consequences of a single decision. It offers a more precise assessment than the predictive tool. Here, the user introduces a single decision (releases from Alarcon, Contreras and Tous) and its consequences are immediately determined (end-of-season storages and downstream water availability). The amount of water to be sent to Albacete and the Mancha Oriental crops can be typed in too. The decision-making tool also shows the inflow forecasts and the reservoir releases foreseen by the predictive tool, to easily establish how the introduced decision was ranked previously.

Any decision can be introduced in the decision-making tool, so it is possible to explore the whole state space of the variables, although options ranked as *feasible* or *likely* by the predictive tool have the best chance to be finally implemented. The same fuzzy arithmetic operations than in the predictive tool are implemented but, in this case, the fuzzy releases calculated by the FRBs are replaced by the ones introduced by the user. Therefore, the tool estimates immediately the consequences of the decision given in order to determine its suitability. This enables the possibility to explore in real-time different alternatives, in order to find out one whose consequences fit the requirements.

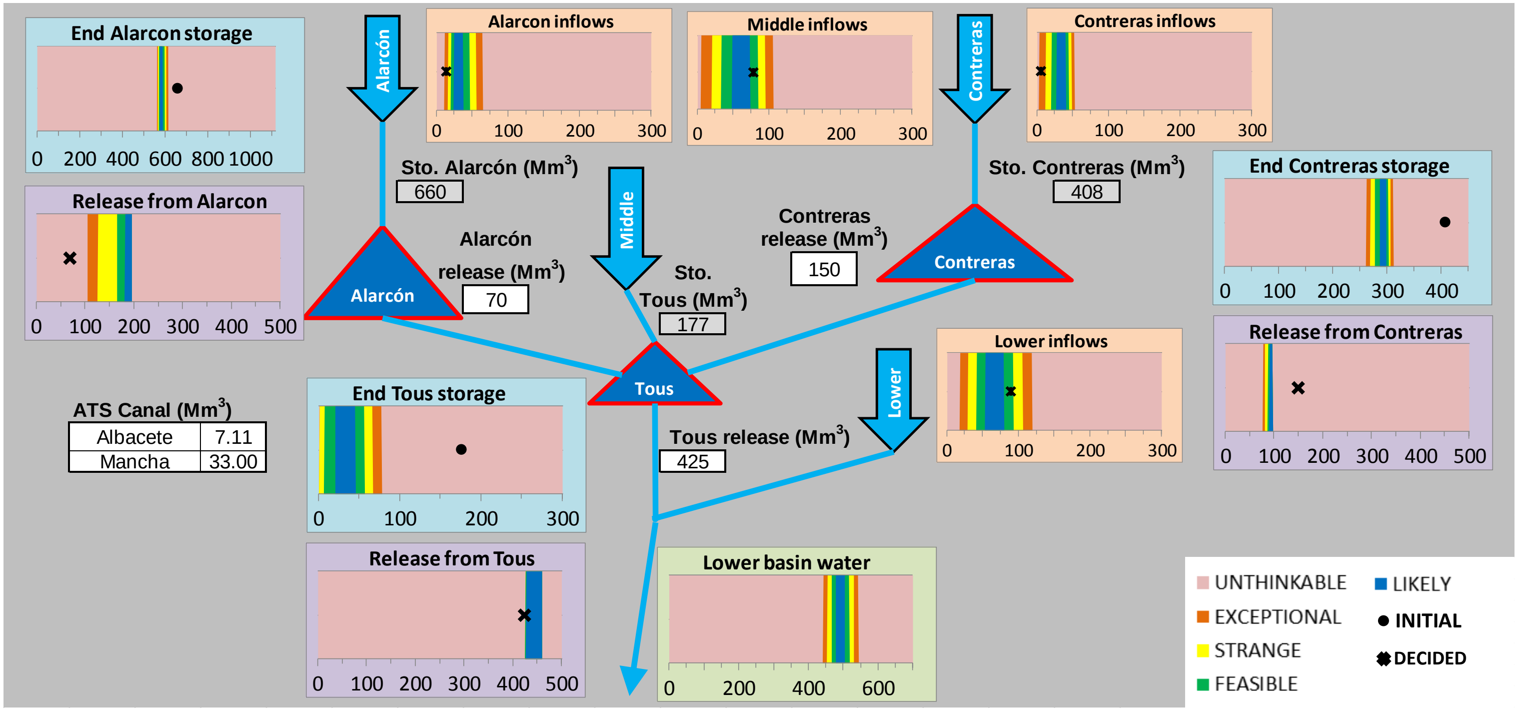


Fig. 7.8: DSS decision-making tool for the Jucar river system

7.2.2. Validation of optimal operating rules

The FRB systems whose outputs have been obtained using the optimization results need to be validated to determine if they offer an improvement with respect to the current situation. For this validation, they need to be compared with the FRB systems reproducing the actual operation.

This comparison has been done for the historical time series (10 years), and for twenty ten-year stochastically-generated time series different from the ones used in the building of the optimal FRB systems. As for the validation of the current operating rules, the optimal FRB systems have been introduced in the STIG_FRB model to obtain monthly time series of results, applying the same downscaling operation and with the same perfect foresight assumption. The CSG-SDDP algorithm has also been run, using the ESPAT_RA tool, for all the comparison time series with the same Jucar river system configuration.

Historical time series

In all the variables obtained, the CSG-SDDP results for the last two years have been dismissed to avoid the influence of the final boundary condition. It has been considered that removing them is better than prescribing ending storage levels or a terminal value for the benefit-to-go function, which would add another source of uncertainty.

The performance of the three alternatives is summarized in Table 7.2. The comparison has been done for the whole period (2003-2013) and for the drought period within it (2005-2008), in order to identify how the alternatives differ in both situations.

As expected, the stochastic programming offers the upper bound in terms of total deliveries, while the current operating rules yield the lowest. The optimal rules represent an intermediate situation, being closer to the stochastic programming (10.53 Mm^3/year below on average) than to the current situation (36.56 Mm^3/year above on average). Both the optimal rules and the stochastic programming show an increase in the deliveries to the agricultural demands with elder rights (all but the Jucar-Turia and the Mancha ones) and a reduction in the others.

Table 7.2: Performance summary of the historical and the optimal operating rules

Demand	Average delivery per hydrological year (Mm³/year)					
	Full period (2003-2013)			Drought period (2005-2008)		
	Historical rules	Optimal rules	Stochastic optim.	Historical rules	Optimal rules	Stochastic optim.
Valencia	85.28	85.28	85.28	85.28	85.28	85.28
Sagunto	6.16	6.16	6.16	6.16	6.16	6.16
Jucar-Turia	20.86	19.62	17.91	2.54	0.00	0.00
Acequia Real	178.62	193.75	194.76	137.46	160.29	152.26
Escalona	28.24	30.34	32.15	23.28	26.18	28.00
Sueca	174.40	186.84	188.61	150.85	168.90	174.41
Cuatro Pueblos	21.71	23.65	24.99	18.50	21.42	24.06
Cullera	103.33	110.58	118.18	89.86	100.64	116.03
Albacete	16.95	16.95	16.90	16.95	16.95	16.84
Mancha	18.51	17.38	16.14	2.00	0.00	0.00
Flowing	19.77	19.83	19.83	19.70	19.83	19.83
Total urban	108.39	108.39	108.34	108.39	108.39	108.28
Total agricultural	565.43	601.99	612.57	444.19	497.25	514.58
Total deliveries	673.82	710.38	720.91	552.58	605.64	622.87

A similar situation is shown for the 2005-2008 drought, in which both the optimal rules and the stochastic optimization outperform the current management. The optimal rules are again closer to the stochastic programming (17.23 Mm^3/year below on average) than to the current situation (53.05 Mm^3/year above on average). The deliveries to the agricultural demands without elder rights decrease, in both the optimal rules and the stochastic optimization, compared to the current operation of the system.

The stochastic optimization shows lower surface deliveries to the Albacete urban demand during the drought, since the Alarcon reservoir becomes empty at some moment. Similarly, the optimal rules show higher deliveries to the Acequia Real demand than the stochastic programming. This is caused by the fact that the latter drawdowns the reservoirs quicker than the optimal rules and, as a result, has to implement higher curtailments than them at the end of the dry period. In this case, the Acequia Real bears the highest deficit among all the demands with elder rights due to having the highest concentration of pumping wells, which they can use to replace surface water.

The storages and releases of the main reservoirs, as well as the total stored water, are presented in Fig. 7.9. As inferred from Table 7.2, the optimal rules (Opt) and the stochastic optimization (ESPAT) present in general lower storage levels, as seen in the total storage plot, indicating that they implement fewer curtailments in advance The optimal rules and the stochastic optimization present similar total storage levels, so their hedging strategies seem to be equivalent from a systemwide point of view. The current operation of the system, on the other hand, shows a cautious situation in comparison with the other alternatives, due to the reluctance of the operators to empty the reservoirs.

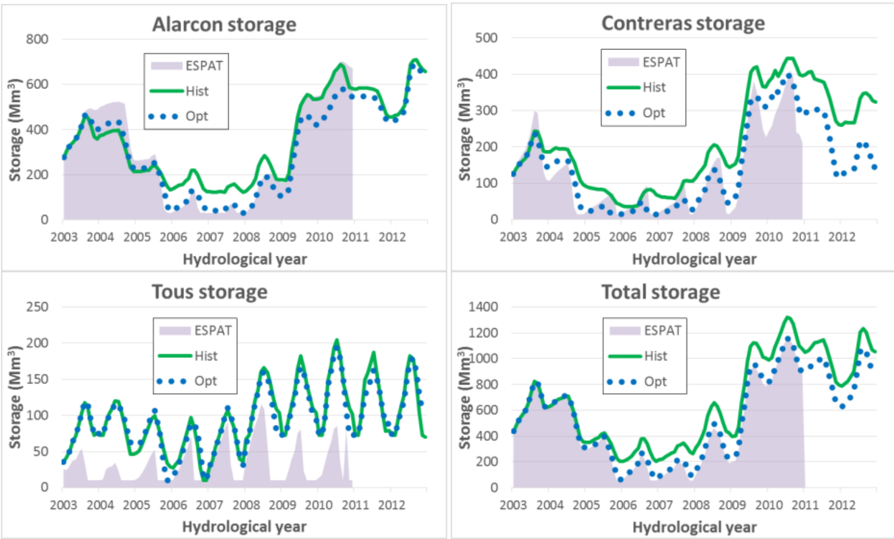


Fig. 7.9: Optimal operating rules validation for reservoir storages

When looking at each reservoir individually, differences between alternatives grow. Both the optimal operating rules and the stochastic optimization tend to store more water in Alarcon before the drought than the current management. This is consistent with the existence of seepage losses in Contreras. Although these losses return to the river several kilometers downstream and can be stored downstream if necessary, Tous is also subject to seepage losses, so eventually part of this resource may be lost.

Consequently, they tend to store more water in Alarcon, in which no seepage losses are found. During the 2005-2008 drought, the optimal rules and the stochastic optimization show a similar behavior, being the current management cautious in comparison. The stochastic optimization is able to store more water in Alarcon than the optimal rules, so higher deliveries can be arranged as noticed in Table 7.2. The situation in Contreras is the opposite than in Alarcon, since both the optimal rules and the stochastic optimization offer lower values than the historical management. This situation seems to be caused also by the seepage losses in Contreras. During the drought period, it can be seen that Contreras' drawdown is quicker in the optimal rules and the stochastic optimization than in the current management, as shown in the graph between 2004 and 2005. This is also caused by the seepage losses, which induces them to first empty Contreras and then Alarcon.

The most significant difference between the current and the optimal rules and the stochastic optimization is the distinctly lower storages obtained in Tous. Since the optimal rules have the same structure as the current ones, the non-written constraint consisting in maintaining a minimum pool level in Tous at the end of the irrigation season is respected. The stochastic optimization algorithm does not consider it. This switch shows advantages due to the seepage losses noticed in Tous.

Comparing the historical and the optimal operating rules, they show differences in how Alarcon and Contreras are balanced while maintaining the same storage levels in Tous. These regard to the implementation of less curtailments in advance more than a significant modification in the upstream reservoir balance (it is modified, but not in a distinct way). This is shown in the fact that the optimal rules present a similar storage decrease in both Alarcon and Contreras. The plots comparing the releases appear in Fig. 7.10.

The optimal rules release more water from Tous than the historical ones during the 2005-2008 drought, especially in 2005, maintaining the same level in the rest of the period. The stochastic programming deliveries raise over the optimal rules in 2006 and 2007, so its hedging strategy is the best among them. A similar pattern is shown in the joint releases from Alarcon and Contreras, although in them the stochastic programming offer higher releases in 2005 too.

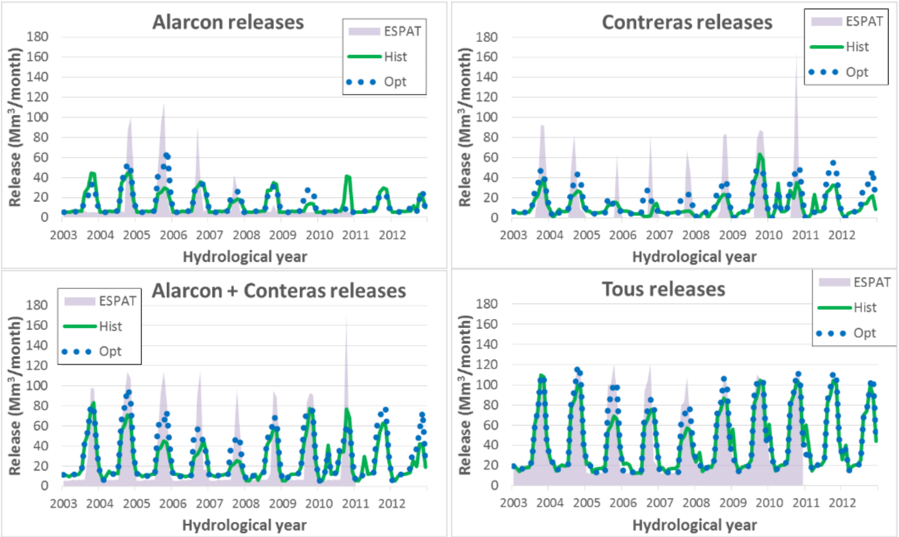


Fig. 7.10: Optimal operating rules validation for reservoir releases

The optimal rules release more water from Alarcon than the historical ones at the beginning of the drought (2005), and then release more resource from Contreras (2006 and 2007). Both optimal alternatives show a similar change in hedging, but stochastic programming is able to maintain high releases from Alarcon also in 2006. This is caused by the stochastic programming storing more water in Alarcon than the optimal rules.

The peaks shown by the stochastic programming releases indicate that this alternative completely re-evaluates the situation month after month and, if necessary, applies a distinctly different decision. On the other hand the optimal rules, as the historical ones, make the decision in May and keep it during the whole irrigation season. This increased number of decisions is able to make an efficient use of the forecasting system employed by stochastic programming, since 1-month forecasts are more accurate than 5-month ones. Moreover, the stochastic optimization tends to store less water in Tous than the other alternatives, avoiding seepage losses. This is compatible with its use as tail reservoir.

Stochastically-generated time series

The same operation options described for the historical time series were found in the majority of the 20 stochastically-generated time series analyzed.

The comparison has been summarized by calculating the empirical distribution associated with the mean annual values of the obtained reservoir releases and demand deliveries, as well as the differences in the total deliveries.

The probability distributions of the releases from Alarcon, Contreras and Tous are shown in Fig. 7.11. For the Alarcon reservoir, both the historical and the optimal operating rules show similar probability distributions, although the latter presents a slight increase. The stochastic programming shows in general similar releases than the other two, although its lower extreme (up to 20%) offers fewer releases.

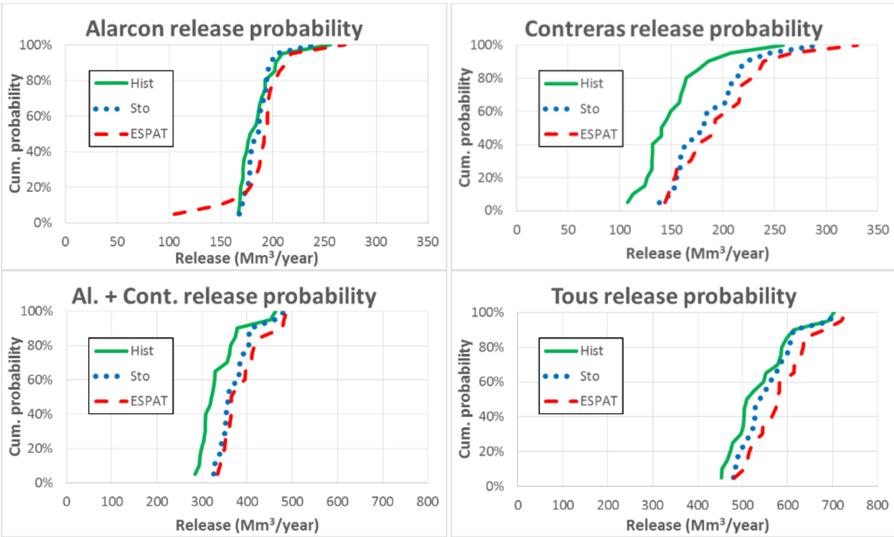


Fig. 7.11: Releases probability distributions of mean annual values

The current rules show less releases from Contreras than the other two alternatives, whose performance is similar (with a slight increase shown by the stochastic programming). The joint releases from the upstream reservoirs are lower in the current operating rules than in the remaining two, which are similar although a slight increase can be noticed in the stochastic programming. The current operating rules offer the lower bound in the Tous releases and the stochastic programming the upper one. However, in contrast with the upstream reservoirs, the optimal rules' probability distribution is closer to the historical one than to stochastic optimization.

The reason why the increase in the upstream reservoir releases noticed between the current and the optimal rules does not show to the same extent in Tous regards to the storage level in Contreras. Since this reservoir suffers seepage losses that return to the river downstream (see Fig. 7.2), higher levels in Contreras mean higher seepage losses and higher downstream flows. Given that the optimal rules lower Contreras, more resource should be release through the Contreras dam to compensate the loss of downstream returns.

An inverse effect can be found comparing the optimal rules and the stochastic programming: they offer similar releases from the upstream reservoirs while the stochastic optimization increases the outflows from Tous. This difference regards to the operation of Tous. In the optimal rules, it has a strict drawdown-refill cycle; while in the stochastic programming it is treated as the tail reservoir of the system. This consideration seems to be the main reason why the stochastic programming outperforms the optimal operating rules.

The probability distributions associated with the deliveries are presented in Fig. 7.12. No differences can be found regarding urban deliveries, with the exception of a slight decrease in the lower extreme of the optimal rules and the stochastic programming. This happens when *everything goes wrong* and all the reservoirs are so empty that even the urban demands need to be curtailed. Being more cautious, the current operating rules do not suffer urban curtailments. This issue reinforces the fact that, although with remarkable advantages, forecasting systems used by stochastic programming are not perfect.

The current operations offer the lower bound, and the stochastic programming results the upper one. The optimal rules are located between them, being closer to the stochastic programming for the lower extreme and to the current operation for the upper one. The pattern shown by the total deliveries (urban plus agricultural) is exactly the same.

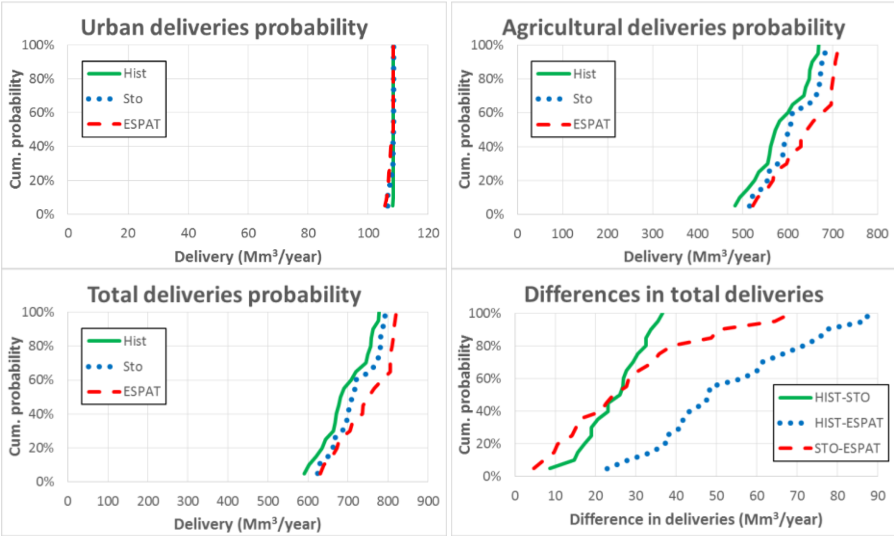


Fig. 7.12: Deliveries probability distributions of mean annual values

The plot with the differences between the alternatives depicts that, for all the inflow scenarios analyzed, the optimal operating rules outperform the current ones. This increase can be measured between 8 and 37 Mm^3/year, with a median value of 25 Mm^3/year. As expected, the stochastic programming always outperforms the optimal rules, between 5 and 67 Mm^3/year, with a median equal to 25 Mm^3/year.

Although on average both the optimal rules and the stochastic programming offer higher deliveries for the whole set of time series analyzed, it should be also compared how severe could the situation be under a drought. For this, the empirical probability distributions corresponding to the annual deliveries for the worst year (the one with the lowest deliveries) have been obtained (Fig. 7.13).

In contrast with the situation depicted for the average values, the current operating policies are not the lower bound for all the time series. It can be seen that, up to 40% of cumulative probability, the historical rules offer the upper bound for both urban and agricultural deliveries, while the stochastic programming drives the worst performance. Above 40%, however, the situation depicted is similar to the one found in the average values, with the historical management outperformed by both the optimal rules and the stochastic programming, with the latter offering the upper bound. Optimal rules offer a similar performance than stochastic optimization.

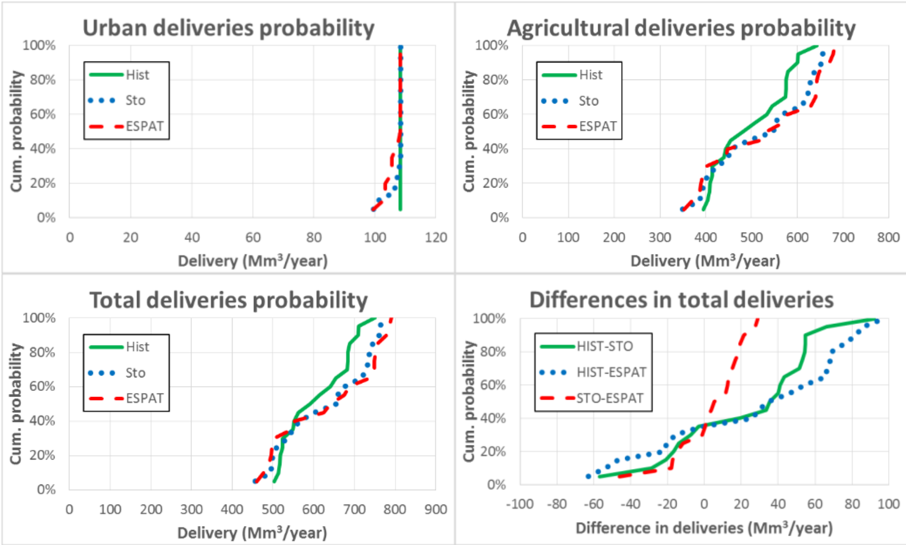


Fig. 7.13: Deliveries probability distributions of the annual value for the worst year

The fact that the optimization algorithm offers the lower bound below 40% percentile and the upper bound above it, as well as its close similarity with the optimal rules, means that less curtailments in advance than the current operation are implemented, as noticed in the analysis of the historical time series. This increase in deliveries at the beginning of a drought shows advantages unless it is so severe. In case of a severe drought, the strategies adopted by the optimal rules and the stochastic optimization may drawdown the reservoirs too fast, so surface water availability could be heavily reduced by the end of the dry period. In contrary, the cautious operation of the current rules distributes better the surface resources.

In spite of the previous remarks, deliveries of the worst year for the optimal rules and the stochastic optimization are higher than the current management for 60% of the analyzed time series. For this reason, it can be concluded that the optimal operating rules are also adequate under drought situations since, for the majority of the time series, even in the worst year of a drought, they were able to outperform the current operation of the system. However, adopting them has some risk of emptying the reservoirs too fast in case of an extreme drought.

It can be summarized that the operation options outlined for the historical inflow time series (implementing less curtailments in advance, using Tous as the tail reservoir and a decision-making month by month in the case of stochastic programming) are maintained for the 20 inflow scenarios analyzed. The optimal operating rules and the stochastic programming are less cautious than the current ones, leading to higher deliveries (so it is worth), but with some risks (curtailments to urban demands and emptying the reservoirs too fast in case of an extreme drought). The limited increase shown by the optimal rules and the stochastic programming means that the current operating rules offer a good performance, although it can be further improved. The improvement obtained by the stochastic optimization means that the current decision-making framework could be enhanced by a monthly decision-making able to completely modify the rules adopted the month before. By doing this, the increase in deliveries with respect to the current rules may be between 22 and 88 Mm^3/year, with a median of 48 Mm^3/year. The demands that benefit from this increase are the ones with elder rights.

7.2.3. DSS tool for optimal decision-making

The DSS tool implementing the optimal operating rules consisted in replacing the expert-based FRB systems employed in the DSS tool previously developed (subsection 7.2.1) by the ones representing the optimal operating rules. The resulting DSS would have exactly the same format and inflow forecasting system than the previous one. The only difference between them would be that the predictive tool would suggest different operation decisions for managing Alarcon, Contreras and Tous. The decision-making tool would remain the same.

An additional tool has been developed to compare and contrast the current and the optimal operating rules and to find overlapping decisions. In case they exist, they could be considered both coherent with the current operation of the system and optimal. If the overlapping zones are known in advance and the system operators are informed about them, the seasonal operation can be improved without the need of changing the operating rules, but just by adding information to the negotiation process. In order to find out and locate the overlapping zones, both operating rules have been combined into a DSS tool similar to the predictive tool (Fig. 7.14).

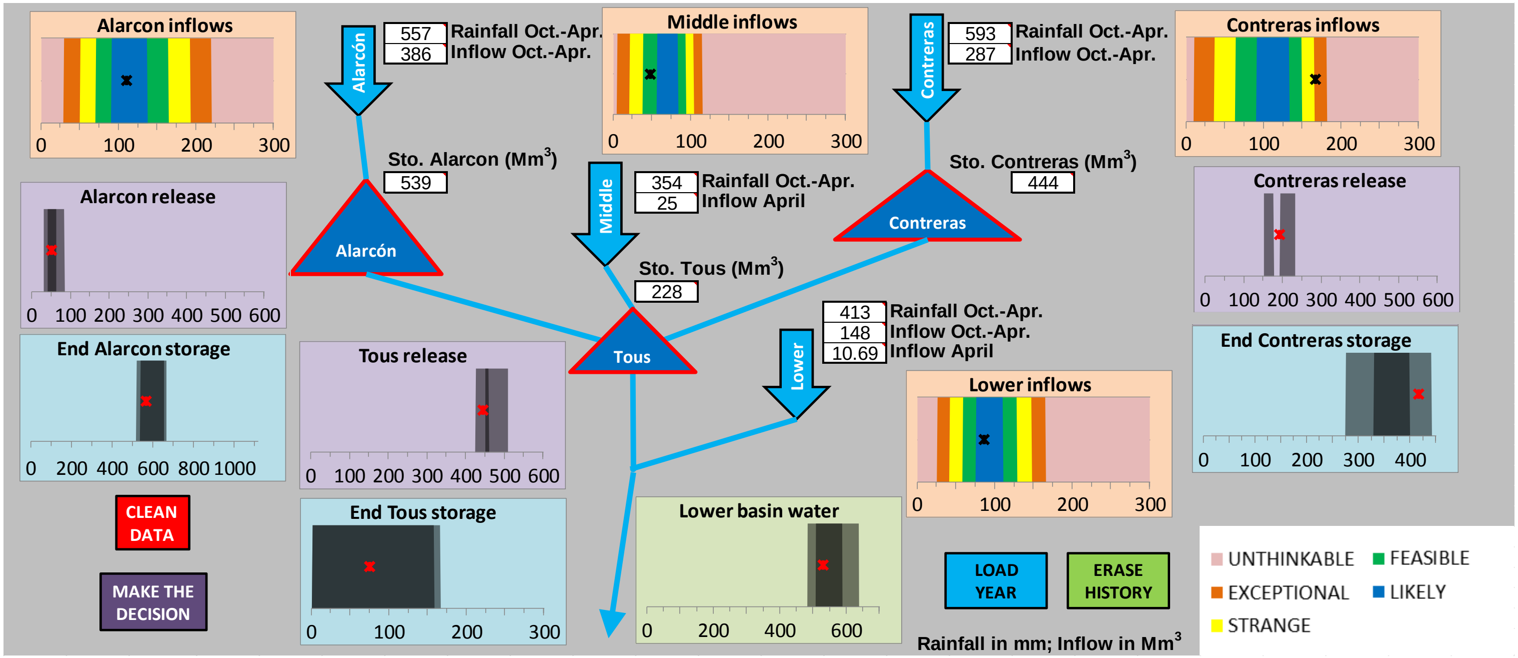


Fig. 7.14: DSS contrast tool

The example data shown in Fig. 7.14 correspond to the irrigation season of the hydrological year 2009 (May-September 2010). The results show the overlaps found between *feasible* decisions obtained using the current and the optimal operating rules. Presenting overlaps for the *feasible* level guarantees they could be acceptable for decision-makers while having some flexibility if possible (overlaps for the *strange* level would be wider but unlikely to be found desirable, while using the *likely* level would lead to narrow overlapping zones or even no overlaps). The color code is a grey-or-black one: grey decisions are optimal or coherent with the current operating rules, while black ones are both current and optimal. Therefore, decisions in the black zone are the most promising ones.

The overlap is not guaranteed, since it can be inexistent (Contreras releases for the example year), or too narrow (releases from Tous for the example year). By showing them, the tool guides the users to focus on the best subset possible within the set of acceptable decisions. It could be considered as an intermediate stage between employing the historical operating rules and switching to the optimal ones, guiding the users to make optimal decision without the need of changing their current practices.

7.3. SUMMARY AND DISCUSSION OF THE DSS DEVELOPMENT

A Decision Support System (DSS) for the seasonal operation of the Jucar river system has been developed combining expert knowledge and historical data. Its development relied on a collaborative framework between researchers and system operators. Fuzzy logic has been used to represent the operating rules followed in the Jucar river seasonal management. Fuzzy regression has been chosen to forecast future inflows based on past and present meteorological and hydrological variables. The DSS was developed to mimic the current seasonal operation of the Jucar river system.

After validating this DSS against historical records, stochastic programming was used to modify the FRB systems representing the operating rules in order to improve their performance. The comparison between both alternatives shows that the rules developed with stochastic programming outperformed the historical ones, although with some risks associated with the possibility to empty too fast the reservoirs.

The DSS tool offers the system operators a way to preview which decisions would be *a priori* adequate under the current or under optimal operating rules, estimating their likely consequences. Furthermore, it compares the suitable decisions under the current management with the ones corresponding to an optimal strategy, helping users to make decisions both optimal and coherent with the current system operation.

The framework presented has been shaped and built in a continuous way during the meetings with the Jucar river system operators. It can be extrapolated to other case studies if the same framework development strategy is adopted. Such a continuous building mechanism is crucial for defining a successful DSS, as new insights on the system and its operation are gained during the process.

The Jucar river system operators declared they were satisfied with the tool defined. The main reasons of their approval, as pointed out by them, were:

- It takes into account the specificities of the Jucar river that affect its seasonal operation.
- They were able to understand the mechanisms implemented by the tool even though they were not familiar with fuzzy logic at the beginning.
- The tool was simple and easy to be used.
- There were not given a single best decision, but a set of suitable alternatives, so they were able to freely choose one of them according to their expertise.

Fuzzy logic has proven to be a suitable approach to acquire and mathematically represent expert knowledge, as well as an adequate way to combine it with historical records and optimization algorithms. The current decision-making processes have been fairly reproduced. The use of an optimization algorithm to turn the decisions into optimal has been successful and straightforward.

In spite of the success of the approach in the Jucar river system, there are several points of improvement. The first is the quality of the fuzzy regression that, although recommended in cases of scarce data, would be improved with more historical records. In particular, the independent variable set was limited, so new data would allow the consideration of more input variables, including cross-correlation of inflows. Neglecting the latter, especially in the Jucar basin in which inflows are cross-correlated, widens the imprecision intervals of the fuzzy inflow projections. The inclusion of cross-correlation should be considered when enough data gets available.

Furthermore, the quality of the FRB systems representing the operating rules would benefit from finer discretizations of the fuzzy inputs, although it could lead to more complex FRB systems and hinder the use of expert judgment. Sen (2010) established that characterizations with more than seven classes would make the resulting FRB difficult to be understood, since differences between the required linguistic terms would be less clear.

Considering that the tool properly reproduced the current decision-making processes of the Jucar river system, the fact that the optimal rules defined outperformed the current ones, the positive feedback about the tool given by the system operators, as well as that the main drawbacks noticed regard to data scarcity, it can be concluded that the framework presented in chapter 4 to define optimal operating rules has been successfully applied.

8. SUMMARY, CONCLUSIONS AND FURTHER RESEARCH

8.1. SUMMARY AND CONCLUSIONS

This PhD thesis presents a stochastic programming algorithm able to perform stochastic optimization runs in large-scale water resource systems taking into account stream-aquifer interactions. As it is based on the Stochastic Dual Dynamic Programming algorithm (SDDP, Pereira and Pinto 1985, 1991), it has been named as CSG-SDDP (Macian-Sorribes et al., 2017). A collaborative framework has also been developed to combine historical records with expert knowledge in a decision support system (DSS) that mimics the current operation of the system. It can contribute to support the seasonal operation of a water resource system (Macian-Sorribes and Pulido-Velazquez, 2017). 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. After the reproduction of the historical system operation, stochastic programming results are used to improve the defined operating rules.

Fuzzy logic is used to derive the implicit operating rules followed by the system operators, based on combining the historical decisions and the expert knowledge obtained in the co-development process. Fuzzy regression is employed to forecast future inflows based on the meteorological and hydrological variables considered by the system operators in their decision-making stages. Afterwards, the CSG-SDDP algorithm is applied to modify the rules, which should then be tested to determine if they improve the historical operation of the system. The developed framework and tools offer the system operators a way to predefine a set of feasible *ex ante* management decisions, and to explore the consequences associated with any single choice. In contrast with alternative approaches, the fuzzy-based method used in this study is able to embed inflow vagueness and its effects in the definition of the system operation. Furthermore, the method is flexible enough to be applied to other water resource systems.

The CSG-SDDP algorithm and the proposed framework have been applied to the Jucar river system in two different ways. In the first application, the algorithm has been used to define economically-optimal conjunctive use strategies for a joint operation of reservoirs and groundwater bodies. The same system configuration as adopted by the CHJ Planning Office in their models (CHJ, 2013) has been employed. The algorithm identified several operation options able to improve the system performance:

- Reducing pumping from the Mancha Oriental aquifer to 240 Mm^3/year on average (including drought years), being partially substituted by 29 Mm^3/year delivered from the Alarcon reservoir.
- Defining pumping curtailments during droughts, in the same way as surface water deliveries are curtailed.
- Using Tous as the tail reservoir of the hydropower system.

In the second application, the framework developed has been used to reproduce the current seasonal operation of the Jucar river system, learning from historical decisions and expert knowledge. Two FRB systems representing the decision-making processes of the Jucar river for the irrigation season (May-September) have been co-developed with the system operators. A water resources management model has been co-developed too, in order to include the variables and processes taken in consideration by decision-makers. The combination of this model and the FRB systems reproducing expert knowledge has been successfully validated against the historical records. A DSS tool has been created to help on the seasonal operation of the Jucar river system considering its current *modus operandi*.

Once the DSS tool was validated, the CSG-SDDP algorithm was run to modify the FRB systems to improve the operating rules. The resulting FRB systems have been compared with the historical ones, as well as with optimal decisions from CSG-SDDP, showing a better seasonal operation of the system due to the following conclusions:

- Less curtailments to the downstream demands can be done at the beginning of a drought.
- The balance between Alarcon and Contreras should be slightly modified.
- If Tous was fully operated as the tail reservoir of the system, deliveries could be increased.

The optimal rules obtained follow the same decision-making processes as the current ones, so they could be applied to real-life without modifying today' *modus operandi* (just the final decision changes). To support the implementation of the optimal rules, the DSS has been updated to work with the FRB systems adapted to the results of the stochastic optimization. Furthermore, the current and the optimal DSS tools have been compared in order to find the overlaps between them, giving the users information about which decisions could be both coherent with the current operating rules and optimal. In this way, system operators could be able to improve the decisions they make without changing the processes and criteria they currently use. However, the improved operating rules have some risk of having a worse worst year in a drought than the current system operation.

It should be noted that the changes in the system operation outlined by the applications to the Jucar river system are complementary, given that they regard to the operation of groundwater bodies as well as surface reservoirs: the ones from the first application (conjunctive use strategies) are valid for managing the main aquifers of the system, while the ones outlined in the second application (improve the allocation schedule for the irrigation season) refer to the operation of the surface reservoirs. Combining them, one could define a complete set of decisions to improve the operation of the Jucar river system. This division is also able to take into account the different time horizons of the impacts of changes in operation, since they usually need more time to show in aquifers than in surface reservoirs.

With respect to the computational requirements of the CSG-SDDP algorithm implementation in GAMS, each EMM increases the dimensionality of the problem as if one more reservoir was added. Nonetheless, no strong computational power was required. In addition, the execution times of the CSG-SDDP algorithm for the Jucar river system were only three times higher than the ones of a deterministic equivalent. This was caused by the use of the Gather-User-Solver-Scatter (GUSS) procedure (Bussieck et al., 2011) implemented in GAMS, which distinctly reduces the time requirements.

Regarding the methodology employed in this PhD thesis, the tools created to properly implement it and the applications developed in the Jucar river system, the following conclusions can be drawn:

1. Stochastic Dual Dynamic Programming (SDDP) and the Embedded Multireservoir Model (EMM) can be combined for the stochastic optimization of large-scale water resource systems. The resulting extended algorithm takes into account stream-aquifer interactions in the definition of optimal operation strategies.
2. Fuzzy logic is able to mathematically represent the operating rules implicitly followed by system operators in the seasonal management of the system, integrating historical data with expert knowledge.
3. The DSS tool presented makes *a priori* assessments regarding management decisions, offering an efficient way to help on the seasonal operation of the system. Combined with inflow forecasting mechanisms, it can be used by the system operators to foresee possible decisions and anticipate likely consequences of them.
4. Stochastic programming, historical records and expert knowledge can be combined for obtaining optimal operating rules respecting the current *modus operandi* of the system.

The applications of these methods and tools to the Jucar river system identified measures to improve its operation considering both the surface and the groundwater component of the system. With regard to them, the following conclusions can be stated:

1. The CSG-SDDP algorithm has successfully considered the stream-aquifer interactions, defining optimal conjunctive use operating rules to increase the economic systemwide efficiency
2. The collaborative framework developed has been able to combine historical data and expert knowledge, mimicking the seasonal operation of the system. The operating rules obtained were then improved employing stochastic programming.
3. The operation improvements suggested by both applications to the Jucar river system cover the operation of surface and groundwater resources.

The optimization results do not present a spectacular increase in benefits or deliveries, as the current operating rules already offer acceptable efficiency levels. This is coherent with the large experience possessed by the Jucar river system planners and operators, improving its operating rules in a continuous way.

8.2. LIMITATIONS AND FURTHER RESEARCH

Despite the successful applications to the Jucar river, the methods and tools developed present some weaknesses. The use of the EMM, for instance, requires to have enough data to characterize the stream-aquifer interaction and the factors that influence it. In addition, it is not capable of representing groundwater heads, so operation options affecting groundwaters need to be assessed using highly-detailed modes (such as finite difference ones) in order to confirm and downscale the results of the EMM.

Furthermore, the mathematical models of the Jucar river system are subject to several sources of uncertainty. An important one is the economic characterization of water demands, done with limited information. Another weakness of the models is that they work under the social planner perspective, seeking to maximize the systemwide efficiency assuming that all the users involved will cooperate for the greater good. However, this efficiency improvement is not symmetrically distributed, so equity issues may arise. These could be examined using, for example, Game Theory (Girard et al., 2016; Madani, 2010), and they could be addressed by employing benefit-sharing mechanisms (Arjoon et al., 2016).

Regarding the DSS tools created for aiding the seasonal management of the Jucar river system, the quality of the fuzzy regressions for inflow projections is hindered by the lack of data, which did not allow the consideration of issues like cross-correlation or the inclusion of additional variables. These regressions should be updated as soon as more data becomes available.

Another limitation of the research is that stationary conditions were used in the analyses developed (first decade of the 21st century). This assumption was conditioned by the necessity of validating the mathematical representation of the current decision-making processes and operating rules. This implies that the improved operating rules are valid for this climate, thus not guaranteeing its validity for future climatic conditions. In order to ensure this, the analysis and thus the rules obtained should be updated using the climate forecasts for the upcoming years.

This update should also include the changes noticed in the rest of the system features: new infrastructures or modifications in the existing ones, changes in demands, modifications in the economic system and thus in the demand functions, changes in energy prices, modifications regarding environmental requirements and so on. Alternatively, a system dynamics approach (e.g. Nikolic, 2015; Simonovic, 2009) could be used to assess adaptive management strategies (although this is out of the scope of this PhD thesis).

In any case, collaborative DSS tools, such as the ones developed in this thesis, are likely to have the best chance to be implemented in reality, as the experts who should use them are directly involved in the process and thus feel confident with the resulting tools.

Considering the methodological developments of this thesis, as well as their applications to the Jucar river system, the following future lines of investigation can be outlined.

- Improvements on the method.
    - Extending the framework developed to multiobjective, many-objective and robust optimization.
    - Combining the operating rules defined with other modeling tools such as agent-based modeling or system dynamics.
    - Defining optimal pricing policies taking into account the water origin (surface, groundwater, reuse water and desalinated water) combining the ESPAT tool with the methodology developed by Macian-Sorribes et al. (2015).
- Improvements on the tools.
    - Programming a GUI for the ESPAT tool.
    - Enhancing the ESPAT tool to perform multiobjective optimizations with non-economic objectives.
    - Including water quality modeling procedures within the ESPAT tool.
    - Validating and further applying the tools and procedures to other river basins.
- Improvements on the case study application.
    - Improving the economic representation of the elements of the conjunctive use model (demand curves, pumping costs and energy benefits), and re-assessing the rest of the elements (EMM, losses, etc.).

- Including additional processes not considered before in the conjunctive use model (emergency wells, l'Albufera, joint management of the Jucar and Turia rivers, prospected water transfer between the Jucar and the Vinalopo, etc.).
- Implementing a method to reproduce the updates and corrections made to the seasonal decisions and embed them into the model.
- Assessing the economic impacts of the decisions carried out by the seasonal operation model.
- Increasing the quality of the fuzzy regressions, and improving the reproduction of the operating rules with respect to the end storage in Tous (finer discretizations).
- Testing the impact of improved inflow forecasting mechanisms such as the ones currently in development under the EU H2020 project IMPREX (www.imprex.eu).
- Including non-stationary climate conditions to re-design and re-assess the operating rules obtained under future hydrological behaviors. In this way, the operating rules could be re-assessed periodically (e.g. each decade or each five years) updating the hydrological conditions and re-starting the calculation processes developed in this thesis again. The evolving conditions of the Jucar river system should also be updated in these re-assessments (infrastructure features, demands, environmental requirements, energy prices, economic features and so on).

9. DISSEMINATION

Dissemination activities performed by the author during his PhD correspond to journal articles, book chapters and conferences. They have been divided into direct dissemination (referring to the dissemination of methods, tools and research results included and discussed in this thesis), indirect dissemination (in which the methods and tools described in this thesis are applied to different case studies or goals than the one of this thesis) and side-research dissemination (not linked with this thesis).

1. **Direct dissemination**

   a. ***Articles in indexed journals***

Title	Improving operating policies of large-scale surface-groundwater systems through stochastic programming
Authors	**H. Macian-Sorribes**, A. Tilmant and M. Pulido-Velazquez
Journal	Water Resources Research (Q1)
Year	2017
Volume	53 (2), DOI: http://dx.doi.org/10.1002/2016WR019573

Title	Integrating Historical Operating Decisions and Expert Criteria into a DSS for the Management of a Multireservoir System
Authors	**H. Macian-Sorribes** and M. Pulido-Velazquez
Journal	Journal of Water Resources Planning and Management (Q1)
Year	2017
Volume	143(1), DOI: http://dx.doi.org/10.1061/(ASCE)WR.1943-5452.0000712

   b. ***Conferences***

Title	DSS Tool for Seasonal Management of a Complex Water Resource System Coupling Expert Criteria, Fuzzy Logic and Stochastic Optimization
Type	Oral presentation (by Manuel Pulido-Velazquez)
Authors	**H. Macian-Sorribes** and M. Pulido-Velazquez
Year	2016
Congress	World Environmental & Water Resources Congress 2016

Title	Optimal operating rules definition in complex water resource systems combining fuzzy logic, expert criteria and stochastic programming
Type	Poster presentation
Authors	**H. Macian-Sorribes** and M. Pulido-Velazquez
Year	2016
Congress	EGU General Assembly 2016

Title	The ESPAT tool: a general-purpose DSS Shell for solving stochastic optimization problems in complex river-aquifer systems
Type	Oral presentation (by **Hector Macian-Sorribes**)
Authors	**H. Macian-Sorribes,** M. Pulido-Velazquez and A. Tilmant
Year	2015
Congress	EGU General Assembly 2015

Title	Design of operating rules in complex water resources systems using historical records, expert criteria and fuzzy logic
Type	Oral presentation (by **Hector Macian-Sorribes**)
Authors	M. Pulido-Velazquez, **H. Macian-Sorribes**, J.M. Benlliure-Moreno and J. Fullana-Montoro
Year	2015
Congress	EGU General Assembly 2015

2. Indirect dissemination

a. Articles in indexed journals

Title	Definition of efficient scarcity-based water pricing policies through stochastic programming
Authors	**H. Macian-Sorribes**, M. Pulido-Velazquez and A. Tilmant
Journal	Hydrology and Earth System Sciences (Q1)
Year	2015
Volume	19, 3925-3935, Open-access available at: http://www.hydrol-earth-syst-sci.net/19/3925/2015/

b. Conferences

Title	Value of Seasonal Fuzzy-based Inflow Prediction in the Jucar River Basin
Type	Oral presentation (by Manuel Pulido-Velazquez)
Authors	M. Pulido-Velazquez and **H. Macian-Sorribes**
Year	2016
Congress	AGU Fall Meeting 2016

Title	Definition of optimal drought-oriented reservoir management policies combining stochastic programming and fuzzy logic
Type	Oral presentation (by **Hector Macian-Sorribes**)
Authors	**H. Macian-Sorribes** and M. Pulido-Velazquez
Year	2015
Congress	International Conference on DROUGHT

Title	Hydro-economic optimization under inflow uncertainty using the SDP_GAMS generalized optimization tool
Type	Oral presentation (by **Hector Macian-Sorribes**)
Authors	**H. Macian-Sorribes** and M. Pulido-Velazquez
Year	2014
Congress	6th IAHS-EGU International Symposium on Integrated Water Resources Management. Evolving Water Resources Systems: Understanding, Predicting and Managing Water-Society Interactions

Title	Definition of scarcity-based water pricing policies through hydro-economic stochastic programming
Type	Oral presentation (by **Hector Macian-Sorribes**)
Authors	**H. Macian-Sorribes**, M. Pulido-Velazquez and A. Tilmant
Year	2014
Congress	EGU General Assembly 2014

Title	Sistemas de Ayuda a la Decisión para la optimización de la gestión de Sistemas de Recursos Hídricos con incertidumbre en las aportaciones
Type	Poster presentation
Authors	**H. Macian-Sorribes** and M. Pulido-Velazquez
Year	2013
Congress	III Jornadas de Ingeniería del Agua: La Protección contra los Riesgos Hídricos

Title	Simulation of operating rules and discretional decisions using a fuzzy rule-based system integrated into a water resources management model
Type	Oral presentation (by **Hector Macian-Sorribes**)
Authors	**H. Macian-Sorribes** and M. Pulido-Velazquez
Year	2013
Congress	EGU General Assembly 2013

Title	Changing the time from month to day: set up of a daily-scale reservoir management model using fuzzy logic
Type	Oral presentation (by **Hector Macian-Sorribes**)
Authors	**H. Macian-Sorribes** and M. Pulido-Velazquez
Year	2012
Congress	3rd SCARCE Annual Conference. Bridging Toxicants, Stressors and Risk-Based Management under Water Scarcity

3. Side-research dissemination

a. Articles in indexed journals

Title	Integrated assessment of the impact of climate and land use changes on groundwater quantity and quality in Mancha Oriental (Spain)
Authors	M. Pulido-Velazquez, S. Peña-Haro, A. Garcia-Prats, A.F. Mocholi-Almudever, L. Henriquez-Dole, **H. Macian-Sorribes** and A. Lopez-Nicolas
Journal	Hydrology and Earth System Sciences
Year	2015
Volume	19, 1677-1693, Open-access available at: http://www.hydrol-earth-syst-sci.net/19/1677/2015/

b. Book chapters

Title	Los mercados de agua en la demarcación hidrográfica del Júcar
Authors	M. Garcia Mollà, C. Sanchís Ibor, **H. Macián Sorribes**, Ll. Avellà Reus and M. Pulido Velazquez
Book	Los mercados de agua en España: presente y perspectivas, 480 pp, Cajamar – Caja Rural
Year	2016
ISBN	978-84-95531-73-5

c. Conferences

Title	Assessing the potential of economic instruments for managing drought risk at river basin scale
Type	Oral presentation (by Manuel Pulido-Velazquez)
Authors	M. Pulido-Velazquez, A. Lopez-Nicolas and **H. Macian-Sorribes**
Year	2015
Congress	AGU Fall Meeting 2015

Title	Effects of drip irrigation on water consumption at basin scale (Mijares River, Spain)
Type	Oral Presentation (by Carles Sanchis-Ibor)
Authors	C. Sanchis-Ibor, **H. Macian-Sorribes**, M. García Molla and M. Pulido-Velazquez
Year	2015
Congress	26th Euro-Mediterranean Conference on Irrigation (ICID 2015)

Title	Impacts of Climate and Land Use Change on the Mancha Oriental Groundwater System, Spain
Type	Oral Presentation (by Salvador Peña-Haro)
Authors	S. Peña-Haro, A. García-Prats. D. Pulido-Velazquez, M. Pulido-Velazquez, A. Lopez-Nicolas and **H. Macian-Sorribes**
Year	2015
Congress	Aqua 2015 42nd IAH Congress

Title	Historical upscaling of the socio-hydrological cycle: Three cases from the Mediterranean Spain
Type	Poster Presentation and Oral Pitch (by **Hector Macian-Sorribes**
Authors	**H. Macian-Sorribes**, M. Pulido-Velazquez and C. Sanchis-Ibor
Year	2015
Congress	EGU General Assembly 2015

Title	Potencial de los modelos hidroeconómicos en la gestión de sistemas de recursos hídricos
Type:	Oral Presentation (by Manuel Pulido-Velazquez)
Authors	M. Pulido-Velazquez, A. Lopez-Nicolas, **H. Macian-Sorribes**, S. Peña-Haro and A. Escriva-Bou
Year	2013
Congress	Jornadas Internacionales de Sistemas Soportes de Decisión en la Planificación y Gestión de Recursos Hídricos 2013

Furthermore, the author has done two international stays during his PhD:

- A two-month stay (September 2013 – October 2013) at the Université Laval (Québec City, Québec, Canadá), under the supervision of Dr. Amaury Tilmant.
- A one-month stay (October 2016) at Deltares – Enabling Delta Life (Delft, Zuid-Holland, The Netherlands), under the supervision of Dr. Marjolein Mens, in the context of the EU IMPREX project and under a Climate-KIC Pioneers Into Practice grant.

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A1. DESCRIPTION OF THE JUCAR RIVER SYSTEM

A1.1. WATER RESOURCES

The Jucar water resources have mainly two origins: surface and groundwater. Regenerated water is currently not allocated to any demand, although several of them have the possibility to use it. Besides, there are neither water transfers nor desalination plants available in the system. Furthermore, emergency wells or emergency pumping from the l'Albufera lake (known as *rebombeos* in Spanish) were not considered due to its extraordinary character.

A1.1.1. Surface water resources

The Jucar River Basin Management Authority (CHJ) Management Plan for the period 2009-2015 (CHJ, 2013) evaluates the surface water resources using the fully distributed hydrological model PATRICAL. The resulting values, for both the 1940/41-2008/09 and 1980/81-2008/09 periods, are included in the following table.

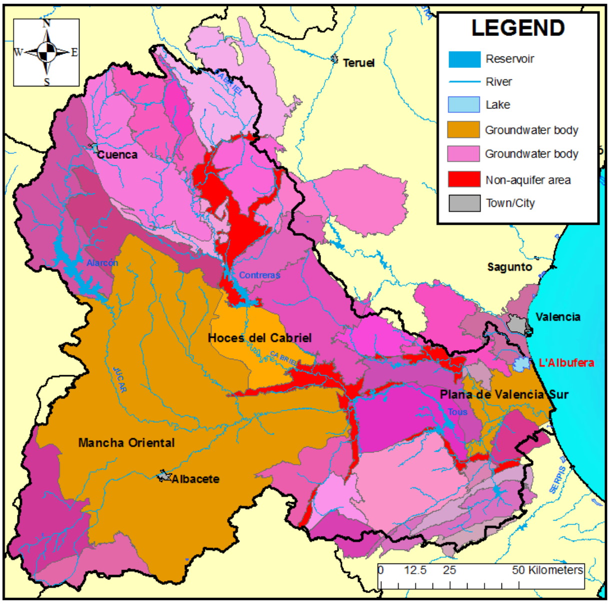
Total surface water resources in Mm^3/year in the Jucar river basin according to the PATRICAL model

1940/41 – 2008/09 (Mm^3/year)			1980/81 – 2008/09 (Mm^3/year)		
Minimum	**Average**	**Maximum**	**Minimum**	**Average**	**Maximum**
675.0	1,747.9	3,362.8	675.0	1,548.1	3,362.8

The surface water resources have suffered a decrease after the 80's. This reduction, found in other Spanish river basins, is known as *the 80's effect*. Due to it, water resource systems analyses in all the Spanish River Basin Management Plans have to be done using two inflow periods: from 1940/41 and from 1980/81.

A1.1.2. Groundwater resources

Groundwater resources play a capital role in the Jucar river. Its surface basin is located totally or partially above 32 groundwater bodies. The most important among them (colored in brown/orange) are the Mancha Oriental, the Hoces del Cabriel and the Plana de Valencia Sur, which hold the more relevant stream-aquifer interactions and most of the wells.

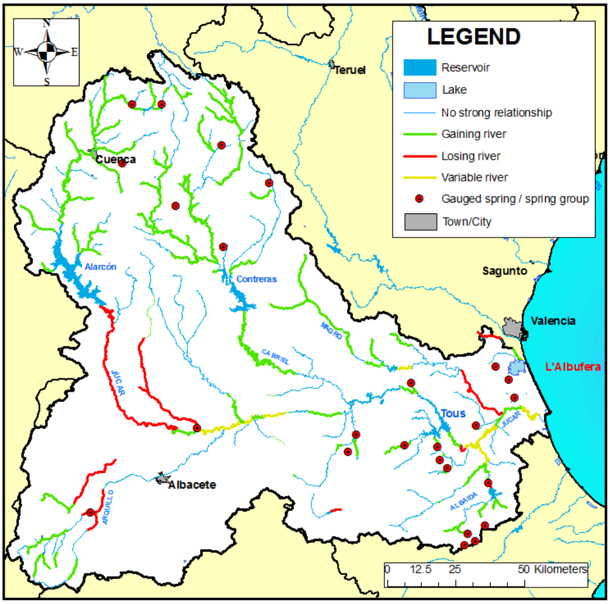


Jucar river basin groundwater bodies

Approximately 80% of the surface water resources enumerated earlier correspond to groundwater discharge either by spring or by stream-aquifer interaction. Besides this water quantity which naturally enters the surface system, according to CHJ (2013), the total amount of groundwater renewable resource in all the aquifers below the Jucar river basin equals 1,661.9 Mm^3/year. Given that 436.8 Mm^3/year cannot be allocated due to environmental reasons, the total amount of groundwater resources allowed to be pumped is 1,225.1 Mm^3/year. This threshold value can be overtaken during droughts, in which agricultural users are allowed to use their emergency wells to complement their supply, as indicated by the Jucar River Drought Management Plan (CHJ, 2007). Despite that, the majority of these available groundwater resources cannot be used due to the lack of pumping capacity.

A1.1.3. Stream-aquifer interaction

The interaction found between surface and ground waters in the basin is depicted in the following figure. The main streams in which a gaining river is found correspond to the upper Jucar river, the upper and middle Cabriel river, part of the middle and lower Jucar river, as well as the upper basins of several Jucar tributaries (Arquillo, Magro and Albaida rivers). The most relevant losing river stream is the middle Jucar river, due to the Mancha Oriental aquifer overdraft, while the lower Arquillo and Magro also infiltrate into groundwater bodies.



Jucar river basin stream-aquifer interaction

Despite having records of more than 3,000 natural springs, only few of them are relevant enough to be gauged regularly. The majority of them are located in the upper basins, although some are found in the borders of the Caroig massif (in the vicinity of Tous), whose discharge is received by the Jucar middle and lower basins.

Springs of *Albufera de Anna* (left) and *l'Ullal Gros* (right)
Sources: www.ayuntamientoanna.es (left) and es.wikiloc.com (right)

A1.2. WATER DEMANDS

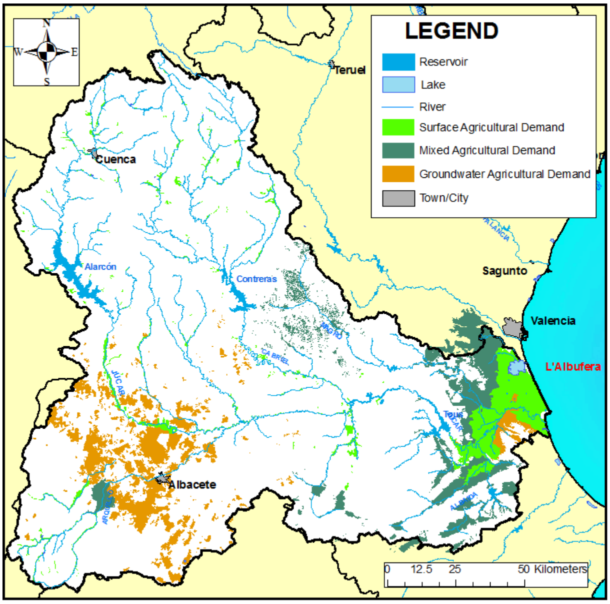
The total consumptive demand of the Jucar river basin is around 1,507 Mm^3 (year 2009), being a heavily committed system (demand similar to surface resource). The demand can be divided in urban, agricultural and industrial.

A1.2.1. Urban demands

The total amount of water required for urban consumption equals 209.9 Mm^3/year at year 2009. Among the 36 Urban Demand Units (UDU) found in the basin, the most important are the cities of Valencia, Albacete and Sagunto, which combine together to 131.5 Mm^3/year.

A1.2.2. Agricultural demands

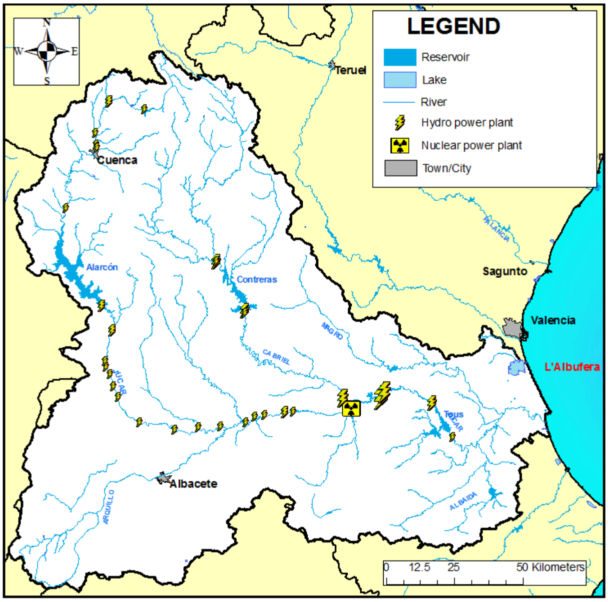
Demanding an amount of 1,347.0 Mm^3 at year 2009, agricultural use is, by far, the largest of the system. The 10 most important Agricultural Demand Units (ADU), combine together to 1,039.8 Mm^3/year. These demands are divided in surface, groundwater or mixed depending on the resource origin employed. Surface and mixed ADUs concentrate in the lower Jucar river, while groundwater ones are located in the Mancha Oriental zone, surrounding the city of Albacete.



Jucar river basin Agricultural Demand Units (ADU)

A1.2.3. Industrial demands

Without considering power production, industrial demands in the Jucar river basin are low in comparison with urban and agricultural uses. Their total amount is located around 27.7 Mm^3/year in year 2009, being most of them supplied by groundwater. With regard to power production, the Jucar River basin holds 1 nuclear power plant (Cofrentes), whose consumption is around 20 Mm^3/year; and 31 hydropower plants.

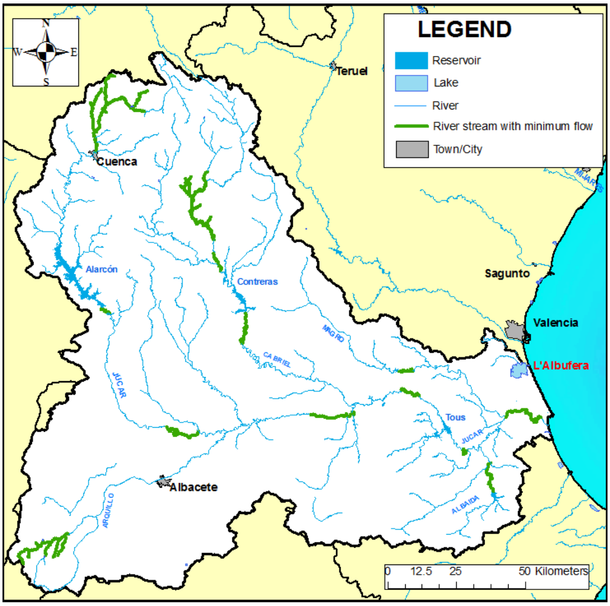


Jucar River basin power plant location

Although not being consumptive demands, hydropower facilities can cause significant modifications in several river streams. Their installed capacities range between 0.2 MW and 628.35 MW, with an aggregated value of 1,271.88 MW. The most important plants (the larger bolt symbols) are the Cofrentes, La Muela de Cortes, Cortes II and Millares II power plants, all of them located near the Cofrentes nuclear power plant.

A1.3. ENVIRONMENTAL REQUIREMENTS

Environmental flows in the Jucar river basin were traditionally set up immediately downstream of the Alarcon, Contreras and Tous reservoirs. As requested by the European Water Framework Directive, the Jucar River Basin Management Plan (CHJ, 2013) increased the streams in which minimum flows were defined to 18. Among them, 12 are defined in the Jucar river, 3 in the Cabriel river and 1 in the Arquillo, Albaida and Magro rivers respectively.



Jucar river basin streams with minimum environmental flows

Moreover, the Jucar River Basin Management Plan defines an environmental requirement for the L'Albufera lake, in order to maintain its current ecosystem status. This requirement has been defined around 167 Mm^3 for the whole year and 148 Mm^3 for the September-April period. This volumes guarantee that the lake entirely renews its water 7 times a year and 6 times between September and April.

A1.4. MANAGEMENT INFRASTRUCTURES

The Jucar river is highly regulated in order to transfer water from wet to dry periods. This requires a significant amount of infrastructure (reservoirs). Furthermore, conveyance facilities (canals) are required to move water from the river streams to the users.

A1.4.1. Reservoirs

The Jucar River basin has a total amount of 11 reservoirs with capacity higher than 1 Mm^3, being 7 of them placed within the Jucar river; 3 in tributary rivers and 1 as an off-stream facility. The most important ones are Alarcon, Contreras and Tous, whose main goal is to regulate the river flows and, in the case of the latter, to protect from flooding.

Jucar river basin reservoir features

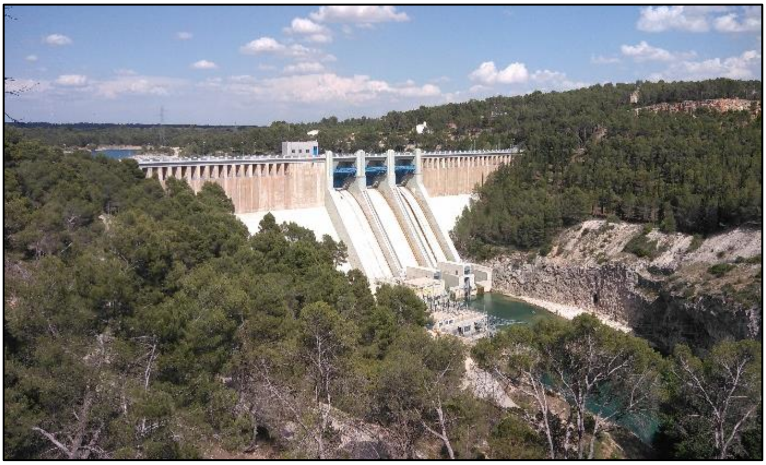
Name	River	Built in	Ownership	Planned capacity	Use
Alarcon	Jucar	1944	USUJ[1]	1118 Mm^3	Cons./ Hydr.
Molinar	Jucar	1989	Iberdrola[2]	4.3 Mm^3	Hydropower
Contreras	Cabriel	1973	State	852 Mm^3	Cons./ Hydr.
Cortes II	Jucar	1989	Iberdrola[2]	118 Mm^3	Hydropower
Naranjero	Jucar	1989	Iberdrola[2]	26.25 Mm^3	Hydropower
Tous[3]	Jucar	1994	State	379 Mm^3	Cons./ Flood
Escalona	Escalona	1997	State	99 Mm^3	Flood
Bellus	Albaida	1998	State	69 Mm^3	Consumptive
Forata	Magro	1968	State	37 Mm^3	Consumptive
La Muela[4]	off-stream	1989	Iberdrola[2]	20 Mm^3	Hydropower
La Toba	Jucar	1944	Union Fenosa[2]	10 Mm^3	Hydropower

[1] *Unidad Sindical de Usuarios del Jucar* (Jucar Users Union). Farmer association

[2] Power company

[3] Built at the same place of the old Tous dam, which was destroyed during a flood in 1982

[4] Water intake and outtake located in the Cortes II reservoir



The Alarcon dam

A1.4.2. Canals

Among the large amount of canals existing in the Jucar river basin, the four main ones are the Tajo-Segura canal, the Maria Cristina canal, the Jucar-Turia canal and the *Acequia Real* (English: Royal Canal) canal.

Jucar river basin canal features

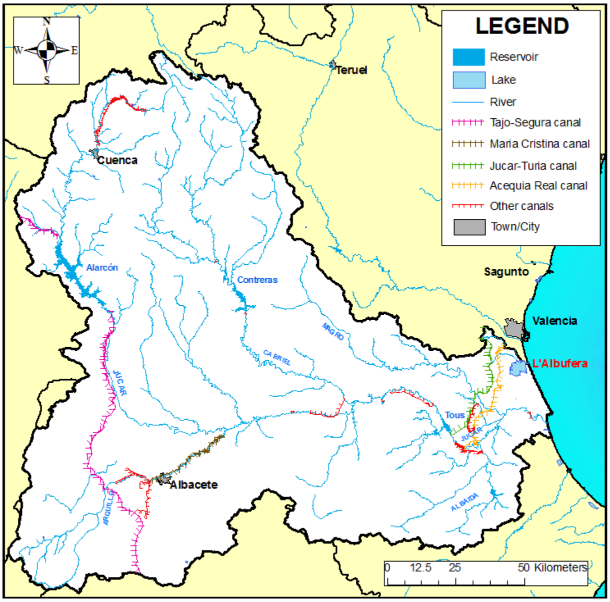
Name	Built in	Ownership	Length	Intake	Ending	Jucar use
Tajo-Segura	1979	State	292 Km	Bolarque reservoir[1]	Talave reservoir[1]	Urban, irrigation[2]
Maria Cristina	1805[3]	State	32 Km	Albacete city	Jucar river	Lagoon drainage
Jucar-Turia	1979	State	60 Km	Tous reservoir	Turia river	Urban, irrigation
Acequia Real	1258[4]	Farmers	60 Km	Antella weir	Albal town	Irrigation

[1] Bolarque reservoir located in the Tajo River basin; Talave reservoir located in the Segura River basin

[2] Built to transfer water between the Tajo and the Segura basins, the CHJ is allowed to convey water to the Albacete city and to the Mancha Oriental farmers to reduce aquifer overexploitation

[3] Year when its building started; the end of the site works is undefined (mid XIX century)

[4] Year when the initial canal was built; its length was enhanced between the 13th century and the 17th century



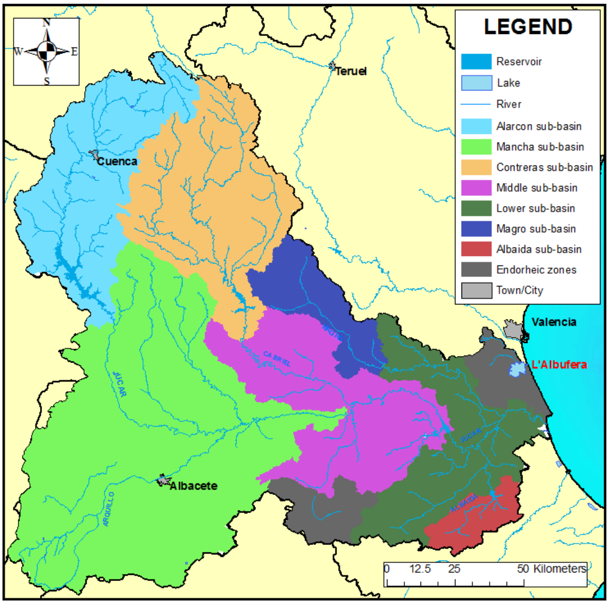
Jucar River basin canals

A2. JUCAR CONJUNCTIVE USE MODEL

A2.1. DESCRIPTION

A2.1.1. Inflows

The inflows employed were obtained from the information provided by CHJ (2013). They were estimated restoring the historical records available in the basin to the natural regime by eliminating the effect caused by man-induced actions such as dam building, pumping, canal diversion, etc. More details about this process can be found in CHJ (2013).



Conjunctive use model sub-basins

Although inflow data records were available between 1980 and 2012, the model runs have been restricted to the 1998-2012 period, since Tous started its operation in 1998. However, the 1980-2012 period was used to set up autoregressive models in order to increase its parsimony.

Conjunctive use model inflows for the 1980-2012 period

A2.1.2. Reservoirs

Eight reservoirs are represented in the model, whose locations can be seen in the following figure. Their maximum allowed storages per month (in Mm^3) and their minimum storages (in Mm^3) are included in next tables. Their characterization was based on the information given by CHJ (2013), reports of the CHJ Operation Office and data provided by the *Centro de Estudios y Experimentación de Obras Públicas* (CEDEX, 2013). In some reservoirs the maximum storage is less than planned due to technical problems (especially in Contreras) and the necessity of having free space to guarantee protection against floods.

With regard to hydropower reservoirs (Molinar, Cortes II and Naranjero), it has been considered that the values provided by CHJ (2013) refer to the management constraints arranged between the CHJ and the Iberdrola power company, rather than their physical constraints. In fact, they do not match with the physical features and the historical records on reservoir levels provided by CEDEX (2013). Consequently, the minimum and maximum storage levels for these have been set as their physical limits.

Conjunctive use model reservoirs

Planning model reservoir maximum allowed storage (Mm³)

Reservoir	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Alarcon	1118	1118	1118	1118	1118	1118	1118	1118	1118	1118	1118	1118
Molinar	4.3	4.3	4.3	4.3	4.3	4.3	4.3	4.3	4.3	4.3	4.3	4.3
Contreras	444	444	444	444	444	444	444	444	444	444	444	444
Cortes II	118	118	118	118	118	118	118	118	118	118	118	118
Naranjero	26.25	26.25	26.25	26.25	26.25	26.25	26.25	26.25	26.25	26.25	26.25	26.25
Tous	72	72	126	195	170	216	240	217	194	171	148	126
Forata	15.9	15.9	25.1	26.6	28.4	28.4	28.4	26.5	26.5	31	21	20.2
Bellus	18.3	18.4	18.3	28.6	28.6	28.6	28.6	28.6	28.6	28.6	28.6	18.3

Conjunctive use model reservoir minimum storages (Mm³)

Reservoir	Alarcon	Molinar	Contreras	Cortes II	Naranjero	Tous	Forata	Bellus
Minimum	30	0.5	15	75	16	10	1	1

A2.1.3. Aquifers and stream-aquifer interaction

The inflows shown previously include the stream-aquifer interactions in natural regime. Consequently, all the EMMs appearing in the Jucar river conjunctive use model reproduce exclusively the anthropic actions (crop infiltration minus pumping). Their response is added to the natural aquifer response in the conjunctive use model to estimate the stream-aquifer interaction.

Five EMMs have been introduced in the model. They represent the Mancha Oriental aquifer, the most important in terms of stream-aquifer interaction; the Hoces del Cabriel aquifer, which receives the seepage losses from Contreras and returns them to the Cabriel river several kilometers downstream; and the Plana de Valencia Sur (PVS) aquifer, which has been divided into three EMMs:

- The PVS North EMM, to hold the pumping abstractions from the Canal Jucar-Turia and Magro demands.
- The PVS Centre EMM, which receives the infiltration from the Acequia Real District and returns part of it to the Jucar river.
- The PVS South EMM, same as the Centre one but referred to the Escalona Irrigation District and the Albaida river

The mathematical characterizations of all the EMMs but the Mancha Oriental one have been obtained from CHJ (2013).

Conjunctive use model EMM parameters

Aquifer model	EMM type	Discharge coefficient α ($month^{-1}$) and action distribution coefficient b		Initial level (Mm^3)[1]	
Mancha Oriental	2-reservoir	3.94 / 0.18	0.0055 / 0.82	0.0	-3,392.0
Hoces del Cabriel	1- reservoir	0.9		8.1	
PVS North	1- reservoir	0		-3,200	
PVS Centre	1- reservoir	0.18		47.6	
PVS South	1- reservoir	0.18		7.3	

1 A negative value implies that, at the start of the analysis period (1998), the aquifer is below its natural state level. A positive one means the opposite, while a zero represents it remains in its natural level

A2.1.4. Canals

The canals included in the model are the ones enumerated in the system description, with the exception of the Maria Cristina canal, whose purpose is not to convey but to drain an endorheic zone. Although the capacities of these infrastructures are higher enough to guarantee the entire supply to their demands, capacity limits have been imposed in sections of the Tajo-

Segura and the Jucar-Turia canals to take in consideration the maximum amount of water they can receive from the Jucar river.

A2.1.5. Environmental flows

Among the environmental requirements outlined in the system description, the ones included in the model correspond to the streams located in the Jucar river downstream Alarcon, in the Mancha Oriental zone, downstream Molinar, downstream Naranjero and downstream the Cullera weir; and the Cabriel river downstream Contreras. The selected locations (eleven), and their monthly requirements in m^3/s, are enumerated in the next table.

Conjunctive use model monthly environmental flows (m^3/s)

Location	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Jucar in Alarcon	2.00	2.00	2.00	2.40	2.40	2.40	2.40	2.40	2.00	2.00	2.00	2.00
Jucar in Mancha	0.60	0.60	0.60	0.72	0.72	0.72	0.72	0.72	0.60	0.60	0.60	0.60
Jucar in Molinar	1.70	1.70	1.70	2.04	2.04	1.70	1.70	1.70	1.70	1.70	1.70	1.70
Cabriel in Contreras	0.80	0.80	0.80	0.96	0.96	0.96	0.96	0.96	0.80	0.80	0.80	0.80
Jucar in Naranjero	1.60	1.60	1.60	1.92	1.92	1.60	1.60	1.60	1.60	1.60	1.60	1.60
Jucar in Cullera	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50

A2.1.6. Demands

Three types of demands have been included in the model: urban, agricultural and industrial, being the latter devoted to energy production via hydropower and nuclear power.

A2.1.6.1. Urban demands

The urban demands considered are four, corresponding to the cities of Albacete, Valencia, Sagunto and the towns and villages of the Mancha Oriental zone. Since the Valencia and Sagunto supplies are shared between the Jucar and other river basins in a fixed percentage, the amount of water included corresponds exclusively to the Jucar share (next table). The annual amounts and their monthly distribution have been estimated using the information given in CHJ (2013).

Conjunctive use model urban demands main features

Name	Source of supply	Demand
Albacete	Surface, but groundwater is possible	17.0 Mm^3/year
Mancha Oriental urban	Groundwater	13.4 Mm^3/year
Valencia	Surface[1]	106.8 Mm^3/year
Sagunto	Surface[1]	7.7 Mm^3/year
[1] The origin corresponds exclusively to the Jucar share of the demand		

Conjunctive use model monthly urban demands (Mm^3)

Demand	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Albacete	1.45	1.39	1.45	1.45	1.29	1.45	1.39	1.45	1.39	1.45	1.45	1.41
Mancha Oriental urban	1.14	1.10	1.13	1.13	1.02	1.14	1.11	1.14	1.10	1.14	1.15	1.11
Valencia	9.08	8.76	9.08	8.97	8.12	9.08	8.76	9.08	8.76	9.08	9.18	8.86
Sagunto	0.64	0.62	0.62	0.62	0.57	0.65	0.64	0.64	0.64	0.70	0.72	0.64

A2.1.6.2. Agricultural demands

Thirteen agricultural demands have been considered, corresponding to the areas depicted in the system description. Approximately 70% of the total demand is located in the lower basin, being the rest placed in the middle basin (the Mancha Oriental demand). The lower basin demands have been separated between rice and citrus in order to adequately handle their different physical and economic features. Their annual and monthly requirements have been estimated using the information appearing in CHJ (2013) and the data facilitated by the CHJ Management Office.

Conjunctive use model agricultural demands main features

Name	Source of supply	Annual demand (Mm^3)
Mancha Oriental agriculture	Groundwater, but 33 Mm^3 switched to surface if possible	332.4
Jucar-Turia	Mixed (39.2 Mm^3 surface and the rest groundwater)	94.2
Magro	Primary surface, but groundwater is possible	8.4
Flowing[1,2]	Surface	19.8

Name	Source of supply	Annual demand (Mm³)
Escalona[1,3]	Surface	42.1
Acequia Real citrus[1,3]	Surface	119.0
Acequia Real rice[1,3]	Surface	75.9
Sueca citrus[1,3]	Surface	14.9
Sueca rice[1,3]	Surface	166.4
Cuatro Pueblos citrus[1,3]	Surface	7.1
Cuatro Pueblos rice[1,3]	Surface	20.3
Cullera citrus[1,3]	Surface	38.0
Cullera rice[1,3]	Surface	85.9
[1] This demand is a member of the Jucar Users Union (USUJ)		
[2] Aggregation of very small users located besides the Jucar river banks		
[3] During droughts they can use emergency wells not considered in the model		

Conjunctive use model monthly agricultural demands (Mm³)

Demand	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Mancha Oriental agriculture	14.6	0.0	0.0	0.0	0.0	20.9	24.6	34.2	46.5	76.5	79.1	35.9
Jucar-Turia	5.7	1.3	2.5	1.2	1.9	5.8	5.0	8.8	15.7	20.6	16.3	9.6
Magro	0.6	0.1	0.2	0.1	0.1	0.4	0.4	0.6	1.4	1.9	1.6	1.0
Flowing	0.0	0.0	0.0	0.0	0.0	0.0	0.0	4.0	3.9	4.0	4.0	3.9
Escalona	3.1	0.8	1.3	0.6	1.1	3.1	2.4	3.4	6.6	8.4	6.9	4.6
Acequia Real citrus	8.8	2.3	3.7	1.8	3.0	8.6	6.9	9.5	18.8	23.8	19.2	12.7
Acequia Real rice	0.0	0.0	0.0	0.0	0.0	0.9	0.7	23.2	14.7	21.8	9.9	4.8
Sueca citrus	1.1	0.3	0.5	0.2	0.4	1.1	0.9	1.2	2.4	3.0	2.4	1.6
Sueca rice	11.2	16.4	15.5	9.5	1.9	3.9	4.6	21.4	22.0	28.1	26.6	5.4

Demand	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Cuatro Pueblos citrus	0.5	0.1	0.2	0.1	0.2	0.5	0.4	0.6	1.1	1.4	1.1	0.8
Cuatro Pueblos rice	0.3	1.5	0.9	0.7	0.4	0.0	0.3	4.5	3.4	3.6	4.1	0.6
Cullera citrus	2.8	0.7	1.2	0.6	1.0	2.7	2.2	3.0	6.0	7.6	6.1	4.1
Cullera rice	4.3	9.1	8.2	4.8	3.8	3.1	2.7	13.2	11.6	11.3	11.8	2.1

The return flows of these demands have been estimated by CHJ (2013), in which the receiving surface water or groundwater body is specified. The return flows have been included in the model graph as shown in its network flow schematic.

A2.1.6.3. Industrial demands

Two types of industrial demands have been considered: cooling water for nuclear power generation and turbined water for hydropower production. The nuclear power plant of Cofrentes takes water from Cortes II. It has a total demand around 20 Mm^3/year with a uniform monthly distribution. Part of the abstracted water returns to the Jucar river immediately upstream of the intake. This situation creates a partially-closed loop, in which only the amount of water lost by evaporation is replaced. The next table shows the monthly cooling demand obtained from CHJ (2013).

Conjunctive use model monthly industrial demands (Mm^3)

Demand	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Cofrentes nuclear	1.6	1.7	1.7	1.6	1.5	1.6	1.6	1.7	1.7	1.9	2.0	1.6

With respect to hydropower production, the 31 power plants existing have been filtered. Power plants with installed capacity lower than 3.5 MW have been discarded. Then, all the power plants upstream of Alarcon or Contreras, as well as off-stream, have been not considered. This sent out the most important hydropower plant, La Muela de Cortes. It has not been considered due to is off-stream location, as well as for being a pumped storage facility unable to be modeled at the monthly scale. The next table shows the main features of the 9 hydropower facilities included in the model. They have been estimated from CHJ (2013).

Conjunctive use model hydropower plants features

Name	Type	Installed capacity (MW)	Net head (m)	Turbine capacity (m^3/s)	Efficiency
Alarcon	Impoundment	16.4	56.0	40.0	0.75
El Picazo[1]	Impoundment	18.0	49.0	46.0	0.81
El Bosque	Run-of-river	8.0	21.5	40.0	0.95
El Tranco del Lobo	Run-of-river	3.8	12.5	42.0	0.75
Cofrentes	Impoundment	124.2	141.6	108.3	0.83
Contreras II	Impoundment	52.5	102.0	80.0	0.66
Cortes II	Impoundment	280.0	96.0	326.0	0.91
Millares II	Impoundment	67.1	137.3	55.0	0.91
Antella-Escalona	Run-of-river	3.6	6.6	40.0	1.00

[1] Associated reservoir not modeled (negligible live storage), so it works as run-of-river in the model

A2.1.7. Economic features

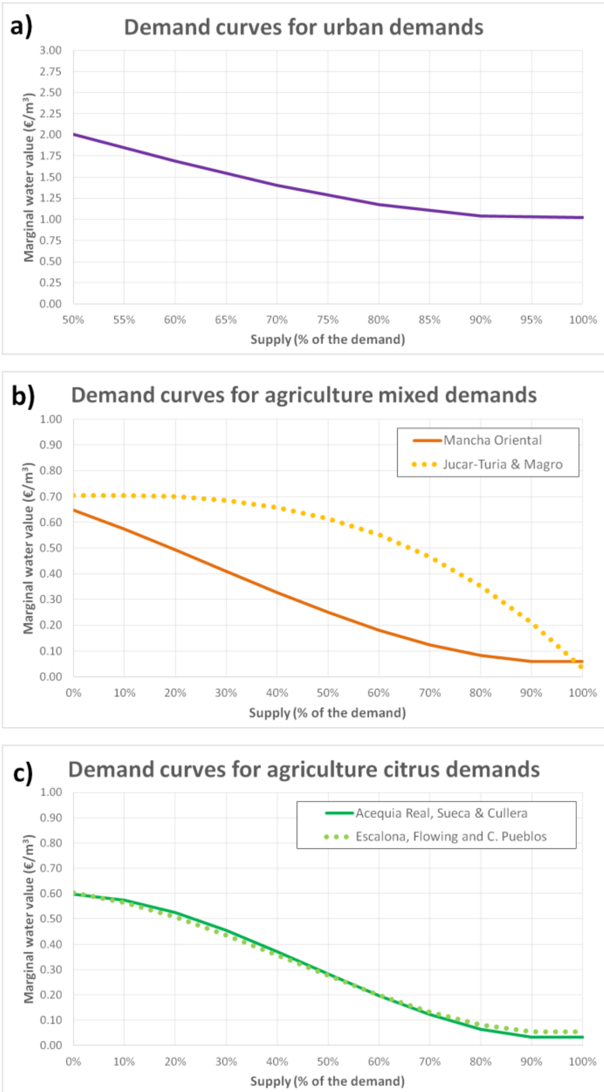
A2.1.7.1. Demand curves

The demand curves employed have been adapted from Pulido-Velazquez et al. (2006b). The adaptations made regard to the requirements of the ESPAT tool (in which the demand curves must be introduced using polynomial equations), several features not acknowledged by the referred study, benefit levels from recent research (Kahil et al., 2016), and bug fixing.

According to the type of water used and the specific economic features, three demand types have been identified: urban demands, agricultural mixed demands and agricultural citrus demands. Inside each demand type, according to Pulido-Velazquez et al. (2006b), different groups of demands were established and the same demand curve was employed for each one:

1. Urban demands
    a. All demands
2. Agricultural mixed demands
    a. Mancha Oriental agriculture demand
    b. Jucar-Turia Canal and Magro demands
3. Agricultural citrus demands
    a. Acequia Real, Sueca and Cullera demands
    b. Flowing, Escalona and Cuatro Pueblos demands

With regard to the rice demands, they have been considered as a constraint, since its supply takes into account environmental reasons concerning l'Albufera, fed by the rice return flows. It has been defined in order to guarantee that the optimization model allocates, at least, the same amounts as done in the current situation. The demand curves are depicted in the following figure.



Demand curves for urban (a), mixed agric. (b) and citrus agric. (c) demands

In the study carried out by Pulido-Velazquez et al. (2006b), urban demand curves were estimated using the point expansion method (Harou et al., 2009; Jenkins et al., 2004). However, this method obtains a demand curve whose values are unbounded when moving to supply levels close to zero, being impossible to estimate the associated benefits by integrating the curve. In order to fix this, an upper bound of 3 €/m^3 was set to the urban demands in order to match the benefit levels to the ones reported in recent research. Then, a polynomial equation in the form $a_1+a_2x+a_3x^2+a_4x^3$ was fitted to the resulting demand curve. The annual equation obtained was downscaled to the monthly scale assuming that that the demand curve has the same shape every month. After this, it has been checked that the benefits estimated using these curves for the historical period 1998-2012 match the levels indicated by recent research (Kahil et al., 2016).

The agricultural demand curves estimated by Pulido-Velazquez et al. (2006b), employed Positive Mathematical Programming (PMP, Howitt 1995), using as base data obtained from previous studies (MMA, 2004; Sumpsi et al., 1998). A polynomial equation was fitted to the demand curves appearing in Pulido-Velazquez et al. (2006b), applying a temporal disaggregation procedure to downscale them to the monthly scale. After this step, it has been checked that these curves provide a benefit level similar to the one reported by recent research (Kahil et al., 2016).

The curve corresponding to the Mancha Oriental agricultural area appearing in Pulido-Velazquez et al. (2006b) has been modified to take into account the impact of the EU Common Agricultural Policy subsidies. It has been considered that these subsidies should be enough, at least, to balance the marginal benefits with the marginal pumping costs at a full supply level. Since the average pumping costs for the 1998-2012 period have been estimated as 0.06 €/m^3 as done in Pulido-Velazquez et al. (2006b), the original demand curve has been lifted 0.06 €/m^3 prior to the treatment process previously described.

A2.1.7.2. Pumping costs

Groundwater heads are required to estimate pumping costs. However, the Embedded Multireservoir Model does not obtain them, but a lumped estimation of the groundwater resource in the aquifer associated with the modeled stream-aquifer interaction. In order to work out this issue, Pulido-

Velazquez et al. (2006b) fitted a regression equation between this estimation of the groundwater storage of the Mancha Oriental EMM (independent variable) and the historical groundwater level records measured at Albacete (dependent variable). A quasi-linear relationship between them was found, so they determined that groundwater levels, and thus pumping costs, can be estimated as a function of the groundwater storages obtained by the corresponding EMM.

A similar linear regression process has been used in this PhD Thesis. However, the relationship has been directly established between the groundwater storage of the EMM of the Mancha Oriental and the resulting pumping cost. In this way, the mathematical process is simpler and does not require the use of groundwater head records, whose relationship with the groundwater storage of the EMM has already been proven.

To fit the linear regression equation, two pairs storage-cost are required. They have been obtained from Pulido-Velazquez et al. (2006b):

- The costs associated when the aquifer was in its natural state were estimated as 0.039 €/m^3.
- The costs at the beginning of the analysis period, 1998, were equal to 0.059 €/m^3.

Using both points, the resulting linear equation is defined as:

$$PC_t = 0.039 - 0.00000577 \cdot \sum_{aqr} G_t^{aqr}$$

Where PC_t pumping costs at time stage and G_t^{aqr} groundwater storage (EMM output). This representation of pumping costs is coarse, but it is an adequate estimate considering the size of the system modeled and the fact that the focus is on surface water. From a systemwide perspective, the approximations driven by this method are adequate, given that the benefit levels and management decisions have been trained and validated against historical records and past research. Consequently, the model's results are considered accurate enough at the systemwide scale.

With regard to the rest of the EMMs, the only one subject to groundwater mining is the PVS North, from which the Jucar-Turia and Magro agricultural demands pump. Nevertheless, the marginal economic value of these demands is way above the pumping costs currently faced by the agricultural users (less than 0.10 €/m^3). Taking this into account, and in the absence of detailed data to estimate the level-cost relationship, the same equation obtained for the Mancha Oriental has been employed in the PVS North EMM.

A2.1.7.3. Energy benefits

The economic evaluation of energy production has been made balancing energy prices with energy generation costs. The energy prices between 1998 and 2012 were obtained from CHJ (2013), and monthly average values were computed (next table). The average value is equal to 0.058 M€/GWh, similar to the marginal production cost of fossil-fueled plants according to Pereira-Cardenal et al. (2014), so the benefits obtained with this procedure would be similar if using the alternative cost method (Young, 2005).

Energy prices assumed for the 1998-2012 period (M€/GWh)

Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
0.061	0.058	0.061	0.060	0.059	0.052	0.052	0.054	0.058	0.060	0.058	0.062

The energy production costs for nuclear power are equal to 0.018 M€/GWh, while hydropower ones are negligible (Pereira-Cardenal et al. 2014). The benefits per unit of energy produced are the energy price less the production costs.

Nuclear power production is a consumptive use, thus requiring a demand curve. Given that the Cofrentes nuclear power plant is able to generate 700 GWh/month (Escriva-Bou, 2012), its total benefits can be estimated as the product between unitary benefits and energy production. A perfectly elastic demand curve has been built for each month, in which the marginal value of water is equal to the total benefits divided by the total water supply. The resulting marginal values are the highest among all the uses found in the system. This is in accordance with the current management policy, in which this demand is considered as a strategic use whose supply must be guaranteed.

Marginal water values of the Cofrentes Nuclear demand (€/m^3)

Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
18.80	16.36	17.58	18.45	19.05	15.02	14.67	14.69	16.47	15.43	13.91	19.27

A2.1.8. Priorities

A priority system must be established in order to run the simulation alternative with STIG_ZB. The goal of the priority system of the conjunctive use model is to reproduce the current operating rules. The priority given to the dead storage in any reservoir is 3000, while the one corresponding to the minimum flows is equal to 2500. With regard to consumptive demands, they have given the priorities in the next table.

Conjunctive use model monthly priorities for consumptive demands

Location	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Albacete	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Mancha Oriental Urban	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Valencia	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Sagunto	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Mancha Oriental agriculture	800	0	0	0	0	800	800	800	800	800	800	800
Jucar-Turia	800	0	0	0	0	800	800	800	800	800	800	800
Magro	1400	1400	1400	1400	1400	1400	1400	1400	1400	1400	1400	1400
Flowing	0	0	0	0	0	0	0	1400	1400	1400	1400	1400
Escalona	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100
Acequia Real citrus	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100
Acequia Real rice	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200
Sueca citrus	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100
Sueca rice	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200
Cuatro Pueblos citrus	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100
Cuatro Pueblos rice	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200
Cullera citrus	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100
Cullera rice	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200	1200
Cofrentes Nuclear	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000	3000

The Cofrentes Nuclear power plant demand has the highest priority given its strategic character. All urban demands have higher priorities than agricultural uses. The Magro has given the highest priority among agricultural demands in order to ensure that Forata is devoted primary to guaranteeing its supply. The same priority has been given to the Flowing demand, since it is a small one that directly takes water from the river according to ancient rights respected in its management. The rice demands are given higher priorities than citrus to ensure they are supplied prior to them. The demands with the lowest priority are the mixed ones (Mancha Oriental agriculture and Jucar-Turia) according to the Alarcon Agreement.

With regard to hydropower production, priorities equal to 1 were given for all the power plants. That ensures the fulfillment of the legal framework, in which no single release is made for hydropower, although all the flows released for consumptive uses are turbinated if it is possible. The priorities and zone division of each reservoir have been treated as calibration parameters.

A2.1.9. Stochastic models

Two stochastic models have been defined in the Jucar river system. An ARMA (1,1) model has been chosen to generate openings and time series, while an MPAR (1) model has been employed to estimate the cuts' parameters associated with the inflows. In order to increase their parsimony, the initially planned 1998-2012 period has been extended to the 1980 year, providing a period between 1980 and 2012.

Since the MPAR (1) model has not been used to generate neither openings nor time series, but as a requirement of the SDDP algorithm, it is only needed to estimate the model's parameters. These are shown in the next tables.

$\delta_{1,oct}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.56	0.00	-0.47	-0.21	0.22	0.03	-0.07
MAM	0.22	0.36	-0.35	-0.29	-0.05	-0.21	0.06
Contreras	0.45	0.56	-0.22	-0.30	0.28	0.09	-0.08
MCT	0.13	0.22	-0.38	-0.21	0.16	-0.15	0.04
Sueca	-0.04	-0.05	0.02	0.00	0.20	-0.26	-0.15
Forata	0.20	0.11	-0.47	-0.39	0.33	-0.18	0.03
Bellus	-0.46	-0.18	0.23	0.25	0.28	-0.03	-0.07

$\delta_{1,nov}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.59	0.26	-0.07	-0.20	0.23	-0.07	-0.08
MAM	-0.35	0.97	0.25	-0.27	-0.18	-0.39	0.29

$\delta_{1,nov}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Contreras	-0.03	0.37	0.70	0.06	-0.16	-0.33	0.19
MCT	0.17	-0.09	-0.26	-0.16	-0.14	-0.11	0.68
Sueca	0.07	0.50	0.13	-0.66	-0.01	-0.12	0.45
Forata	0.01	0.65	0.18	-0.72	-0.57	0.27	0.34
Bellus	-0.08	-0.07	0.16	0.25	-0.55	0.21	0.65

$\delta_{1,dec}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.32	-0.08	0.10	0.08	0.16	0.18	-0.38
MAM	-0.29	0.55	0.42	0.07	-0.07	-0.21	-0.07
Contreras	-0.10	-0.03	0.40	0.23	-0.09	0.66	-0.53
MCT	-0.42	-0.27	0.11	0.68	-0.53	0.63	-0.28
Sueca	-0.36	-0.17	0.26	0.83	-0.35	0.27	-0.54
Forata	-0.22	0.06	-0.13	0.37	-0.80	1.27	-0.31
Bellus	-0.22	-0.16	0.20	0.48	-0.08	-0.13	0.03

$\delta_{1,jan}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	1.14	-0.08	-0.60	0.05	0.04	0.14	-0.16
MAM	0.10	0.77	0.01	0.10	-0.28	0.12	-0.01
Contreras	0.90	-0.07	-0.19	0.08	-0.02	0.10	-0.15
MCT	0.20	-0.12	0.10	0.73	-0.01	-0.03	-0.02
Sueca	-0.12	-0.11	0.31	0.14	0.43	0.27	-0.01
Forata	0.45	-0.17	0.05	0.19	-0.39	0.38	-0.02
Bellus	0.04	0.07	0.06	0.13	0.10	0.18	0.28

$\delta_{1,feb}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	-0.45	-0.18	1.39	-0.24	-0.27	-0.46	0.41
MAM	0.18	0.81	-0.28	-0.22	0.73	-0.06	-0.18
Contreras	-1.30	-0.11	2.31	-0.09	-0.28	-0.41	0.34
MCT	0.28	-0.09	-0.37	0.69	-0.04	-0.24	0.12
Sueca	0.29	-0.10	-0.39	-0.01	0.81	-0.01	-0.01
Forata	0.12	-0.11	-0.22	-0.19	-0.18	0.50	0.86
Bellus	0.13	-0.09	-0.13	0.11	0.33	-0.19	-0.02

$\delta_{1,mar}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.58	0.17	-0.03	-0.10	-0.39	0.36	0.30
MAM	-0.19	0.77	0.02	-0.32	-0.35	0.20	0.31
Contreras	0.09	0.18	0.65	-0.11	-0.24	0.23	0.23
MCT	-0.23	-0.02	0.24	0.47	0.06	0.05	0.04
Sueca	0.26	0.12	-0.55	-0.13	0.76	0.47	-0.07
Forata	-0.18	0.09	0.27	0.11	0.26	0.60	-0.24
Bellus	-0.07	0.05	-0.01	0.10	0.13	-0.01	0.68

$\delta_{1,apr}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.42	-0.06	0.04	0.03	0.12	0.24	-0.25
MAM	-0.61	0.63	0.51	-0.21	0.13	0.34	-0.25

$\delta_{1,apr}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Contreras	-0.08	0.06	0.60	0.04	0.15	0.46	-0.21
MCT	0.49	-0.25	-0.83	0.33	-0.06	0.53	0.24
Sueca	-0.23	0.12	0.17	0.05	0.53	0.45	-0.08
Forata	0.02	0.17	-0.07	0.18	0.15	0.36	-0.32
Bellus	-0.31	-0.04	0.33	0.23	0.14	0.02	0.42

$\delta_{1,may}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.68	-0.04	-0.03	-0.05	-0.12	0.06	-0.06
MAM	-0.05	0.27	0.45	-0.24	0.10	-0.06	0.03
Contreras	0.07	-0.03	0.87	-0.09	-0.25	-0.08	0.12
MCT	0.58	0.37	-0.86	0.50	0.14	-0.13	0.24
Sueca	0.06	0.28	0.16	0.37	0.22	-0.37	0.22
Forata	0.18	0.01	0.43	0.19	0.08	0.04	0.05
Bellus	0.02	0.12	0.02	0.22	0.58	-0.56	0.30

$\delta_{1,jun}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.35	-0.17	0.60	-0.12	-0.29	0.11	0.19
MAM	0.16	0.52	-0.01	-0.22	-0.09	-0.15	0.56
Contreras	-0.33	-0.08	1.22	-0.10	-0.06	-0.05	0.05
MCT	-0.02	-0.13	-0.16	0.51	-0.37	-0.11	0.51
Sueca	0.10	-0.41	0.31	0.01	1.04	-0.41	0.00
Forata	-0.24	0.07	0.14	-0.41	-0.54	0.76	0.33
Bellus	-0.03	-0.13	0.20	-0.05	-0.23	0.02	0.73

$\delta_{1,jul}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.78	-0.11	-0.18	-0.23	0.21	0.21	0.17
MAM	-0.51	0.55	-0.09	-0.18	0.16	0.67	-0.47
Contreras	-0.31	0.05	1.13	-0.08	0.00	0.06	-0.04
MCT	0.00	0.06	-0.13	0.13	-0.36	-0.27	0.59
Sueca	-0.01	-0.08	-0.11	-0.18	1.20	0.39	-0.71
Forata	-0.36	0.12	0.24	0.14	-0.35	0.61	0.26
Bellus	-0.42	0.04	0.26	0.29	-0.19	0.13	0.66

$\delta_{1,aug}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.57	-0.35	0.04	-0.20	0.08	0.06	-0.19
MAM	-0.48	0.41	0.30	0.06	0.13	0.03	0.07
Contreras	0.01	-0.06	0.98	-0.03	0.02	-0.10	-0.01
MCT	-0.41	-0.16	-0.25	0.43	0.18	0.19	0.24
Sueca	-0.14	-0.03	0.02	0.13	1.03	0.18	-0.26
Forata	-0.15	-0.10	-0.24	-0.16	0.08	1.14	-0.25
Bellus	-0.03	0.00	-0.12	-0.01	0.14	0.35	0.64

$\delta_{1,sep}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.81	0.00	0.14	-0.03	0.01	-0.19	0.25
MAM	-0.27	0.47	0.45	0.43	-0.11	0.10	-0.18

$\delta_{1,sep}$	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Contreras	0.04	0.06	0.97	0.09	-0.09	-0.09	0.05
MCT	0.47	0.14	-0.43	0.25	0.25	-0.05	-0.02
Sueca	-0.24	-0.38	0.52	0.57	0.41	0.13	0.06
Forata	-0.06	-0.37	-0.08	-0.17	0.17	0.03	0.53
Bellus	-0.30	-0.37	0.35	0.46	0.13	0.03	-0.13

The ARMA(1,1) model has been picked up in order to cope with the long-run significant autocorrelation coefficients found in the Jucar river system. The number of data records per parameter is equal to 8.93, low but above the threshold of 6 pointed out by Salas et al. (1980). A total amount of 20 openings and 20 time series has been generated using MS Excel.

δ_1	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.76	-0.08	-0.02	-0.23	0.03	-0.08	0.12
MAM	-0.19	0.80	0.27	0.24	-0.04	-0.06	-0.10
Contreras	-0.03	-0.05	0.79	-0.32	0.05	0.03	0.11
MCT	0.10	0.06	-0.14	0.53	0.21	-0.23	0.20
Sueca	-0.09	-0.12	0.04	-0.18	0.66	0.01	0.20
Forata	-0.07	-0.14	0.03	-0.21	0.16	0.71	0.03
Bellus	-0.13	-0.12	0.04	-0.04	0.15	0.02	0.70

ω_0	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	0.65	0.00	0.00	0.00	0.00	0.00	0.00
MAM	0.02	0.76	0.00	0.00	0.00	0.00	0.00
Contreras	0.33	0.11	0.36	0.00	0.00	0.00	0.00
MCT	0.09	0.01	0.16	0.81	0.00	0.00	0.00
Sueca	0.07	0.25	0.15	0.18	0.68	0.00	0.00
Forata	0.18	0.18	0.18	0.23	0.16	0.68	0.00
Bellus	0.07	0.13	0.11	0.24	0.21	0.20	0.60

ω_1	Alarcon	MAM	Contreras	MCT	Sueca	Forata	Bellus
Alarcon	-0.01	-0.08	-0.13	-0.12	0.01	-0.09	0.14
MAM	0.02	0.33	0.11	0.21	-0.08	-0.11	-0.03
Contreras	-0.05	0.00	-0.01	-0.21	0.09	0.03	0.12
MCT	0.02	0.22	0.02	0.20	0.17	-0.21	0.11
Sueca	-0.11	0.03	0.08	-0.14	0.17	0.11	0.15
Forata	-0.06	0.01	0.04	-0.09	0.25	0.20	-0.01
Bellus	-0.05	-0.03	0.01	-0.06	0.22	0.09	0.16

A2.2. CALIBRATION

The conjunctive use model calibration has two main objectives:

- Determine if the system representation assumed is adequately reproducing reality.

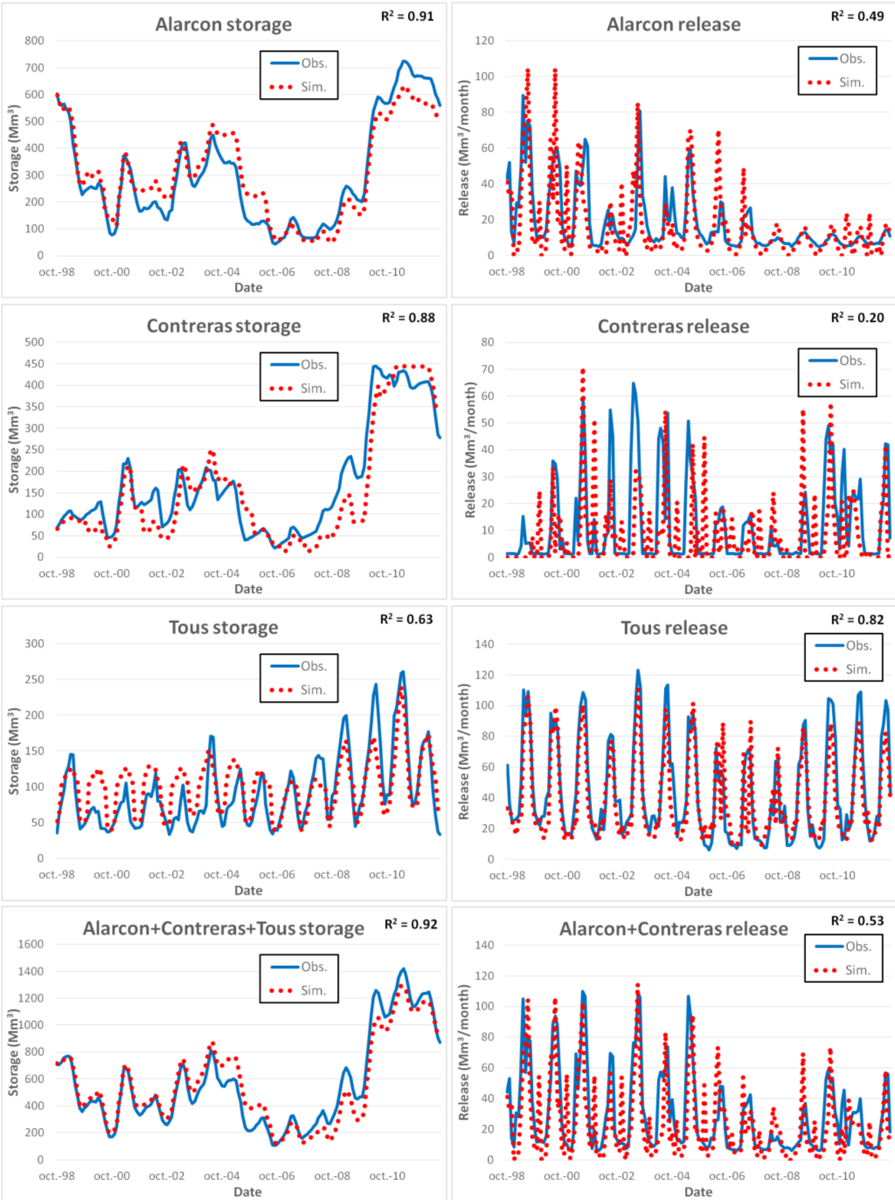
- Establish if the management rules assumed by the simulation model are a good estimation of the current operating rules.

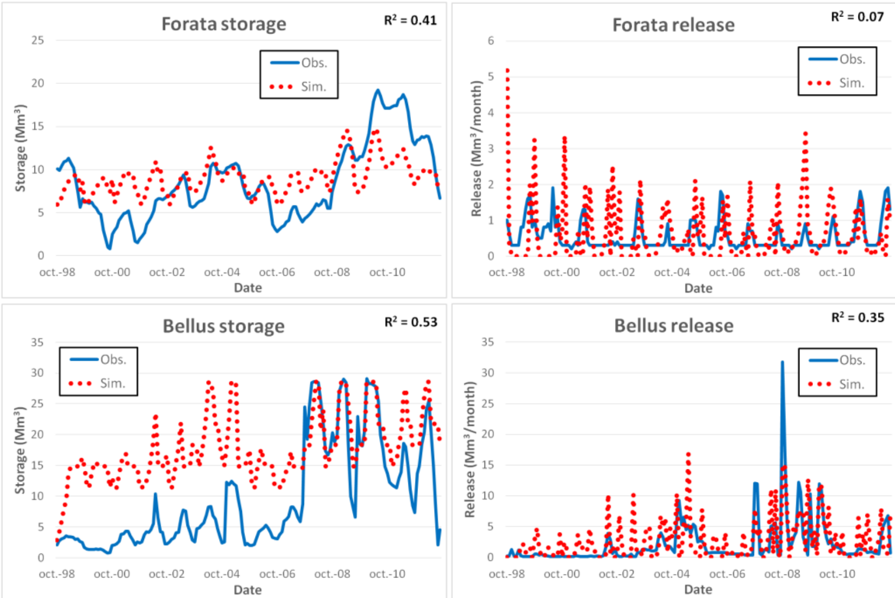
Due to the short length of the available data (1998-2012 in the best case), the whole records available have been used in the calibration. These consisted of storage and releases in the main reservoirs of the system (Alarcon, Contreras and Tous), streamflows in several points of the basin, deliveries to the system's demands and long-term average water use intensity and water productivity in the hydropower plants. These average values and records have been obtained from the CHJ Operation Office, the Jucar River Basin Management Plan (CHJ, 2013), and CEDEX (2013).

A2.2.1. Consumptive use reservoirs

Calibration of the main reservoirs' storage is rather good, with an average R-squared value of 0.80 (0.91, 0.88 and 0.63). The model reproduction of the monthly releases from Contreras (0.20) is worse than Alarcon (0.49) and Tous (0.82), although Contreras storage is adequately fitted, which implies that the total outflows from the reservoir (turbined, released through the dam and lost by seepage) are fairly reproduced as a whole.

With respect to the rest of the reservoirs, the ones devoted exclusively to hydropower (Molinar, Cortes II and Naranjero) have not been trained due to the impossibility to capture the steep drawdown-refill cycles, caused by its hydropower operation, in a basinwide monthly-scale model. Alternatively, the productivity and use intensity of their associated hydropower plants has been trained with adequate results. The two remaining reservoirs (Forata and Bellus), have R-squared coefficients of 0.41 and 0.53 for the storage and 0.07 and 0.35 for the releases. Given its reduced capacity and local relevance, no more efforts were made to calibrate them.


Alarcon storage
R² = 0.91
Obs.
Sim.
Storage (Mm³)
800
700
600
500
400
300
200
100
0
oct.-98
oct.-00
oct.-02
oct.-04
oct.-06
oct.-08
oct.-10
Date
Alarcon release
R² = 0.49
Obs.
Sim.
Release (Mm³/month)
120
100
80
60
40
20
0
Date
Contreras storage
R² = 0.88
Obs.
Sim.
Storage (Mm³)
500
450
400
350
300
250
200
150
100
50
0
Date
Contreras release
R² = 0.20
Obs.
Sim.
Release (Mm³/month)
80
70
60
50
40
30
20
10
0
Date
Tous storage
R² = 0.63
Obs.
Sim.
Storage (Mm³)
300
250
200
150
100
50
0
Date
Tous release
R² = 0.82
Obs.
Sim.
Release (Mm³/month)
140
120
100
80
60
40
20
0
Date
Alarcon+Contreras+Tous storage
R² = 0.92
Obs.
Sim.
Storage (Mm³)
1600
1400
1200
1000
800
600
400
200
0
Date
Alarcon+Contreras release
R² = 0.53
Obs.
Sim.
Release (Mm³/month)
140
120
100
80
60
40
20
0
Date



A2.2.2. Hydropower plants

Power plant	Production (GWh/year)		Water use intensity (m^3/Kwh)		Water use productivity (€/m^3)	
	Observed[1]	Simulated	Observed[2]	Simulated	Observed[2]	Simulated
Alarcon	-	14.34	9.00	13.01	0.008	0.004
El Picazo	-	24.16	-	9.26	-	0.006
El Bosque	-	8.91	20.00	17.99	0.004	0.003
El Tranco del Lobo	-	4.09	33.00	39.18	0.003	0.002
Cofrentes	51.00	33.49	4.00	3.13	0.015	0.019
Contreras II	-	13.47	6.00	7.00	0.009	0.009
Cortes II	120.00	119.26	5.00	4.27	0.013	0.014
Millares II	141.00	148.64	4.00	3.06	0.015	0.020
Antella - Escalona	-	5.85	-	55.66	-	0.001

[1]: data obtained from Iberdrola

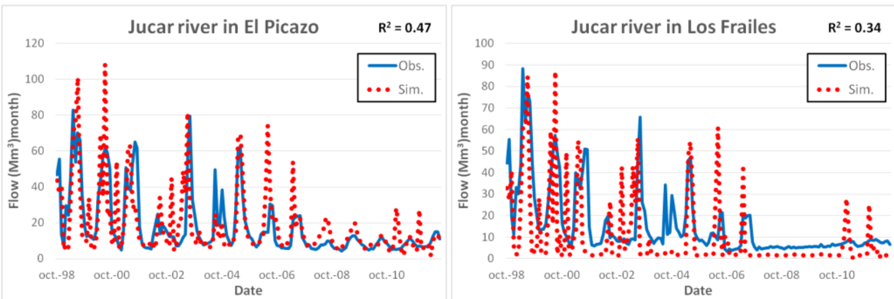
[2]: data obtained from the CHJ

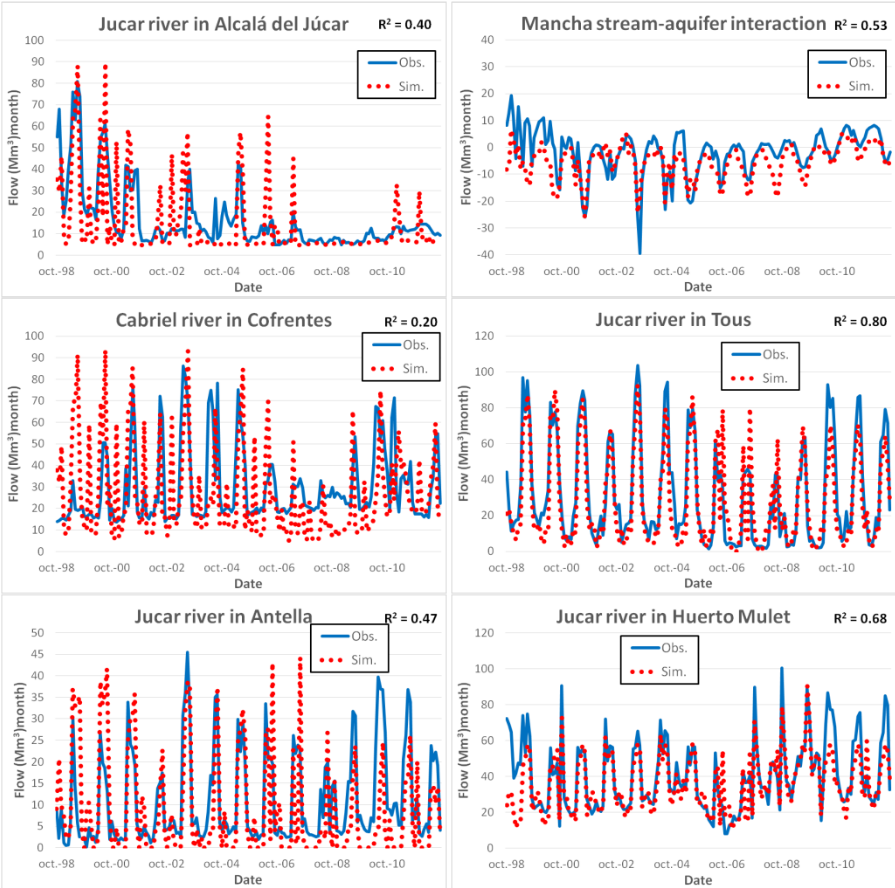
A2.2.3. Streamflows

Several gauging stations have been used to calibrate the model. In the middle Jucar river basin, the calibration results are so-so, with an average R-squared of 0.40 (0.47 downstream of Alarcon, 0.34 in Los Frailes and 0.40 in Alcala del Jucar). The calibration of this zone is hindered by two limitations of the model:

- The model assumes that the inflows and the stream-aquifer interaction exchanges are added to the Jucar river at specific points, while the real stream-aquifer interaction is diffuse.
- The model considers that the features of the Mancha Oriental demand remain steady during the whole period. In fact, the high crop mosaic variability induces large water demand variability. Although a more detailed representation of this demand could have been introduced, it would increase the complexity of the model and, more important, it would make it difficult to extract operating rules. The demand characterization introduced, based on CHJ (2013), reflects the long-term patterns, and thus has been considered representative.

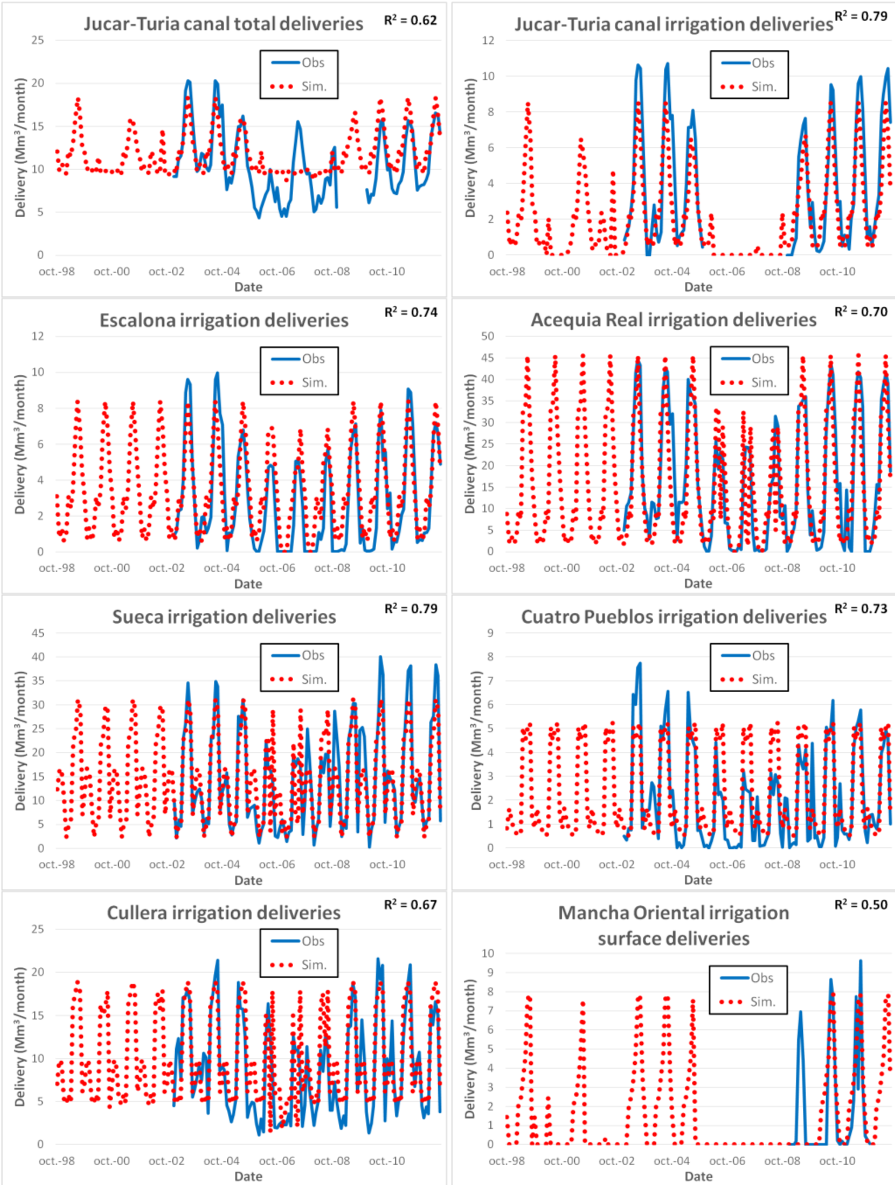
The streamflow records in the lower Jucar river basin show an adequate calibration, with an average R-squared value of 0.65 (0.80 in Tous, 0.47 in Antella and 0.68 in Huerto de Mulet). The records in Antella measure the discharge over the Antella weir, and may be affected by the canal diversions and returns located in the area. Huerto de Mulet records are affected by the downstream Sueca weir, which can partially inundate the location of the gauging station.





A2.2.4. *Demand deliveries*

To calibrate the demand deliveries, the model results on citrus and rice deliveries for the same demand have been added, since the available records do not distinguish between them. The delivery calibration offered by the model is good, with an average R-squared value of 0.69 ranging between 0.50 and 0.79. The lowest value corresponds to the surface deliveries to the Mancha Oriental demand, for which only 3 years of data were available. This adequate reproduction of the demand deliveries is crucial, since it will directly affect the economic benefits obtained.



A2.2.5. Summary

The model is fairly reproducing the storages in the three main reservoirs (Alarcon, Contreras and Tous), the long-term energy production and benefits of the hydropower plants, as well as the consumptive demands. The model's best calibration of system flows has been found in the lower basin (streamflows and deliveries), in which the majority of the water-consuming economic activities are located. The model successfully represents the processes found in the most important and complex part of the system, enhancing the validity of its assessments.

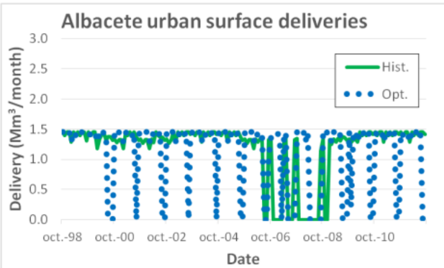
The so-so representation that the model provides in the middle Jucar seems to be caused by limitations of the modeling procedures assumed rather than bad calibration. However, the long-term trends are adequately reproduced. Increasing the quality of the calibration in this zone will imply the adoption of more detailed techniques, which would have a negative impact on the systemwide vision of the model.

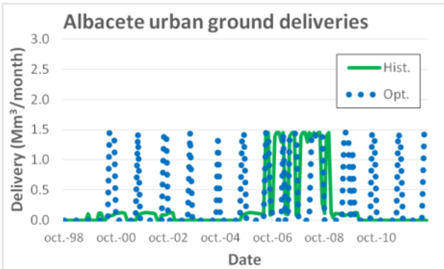
The points in which the model calibration could be improve are the representation of the Contreras reservoir outflows (although the overall resource release is adequately represented), the calibration of the storages associated with the hydropower reservoirs, as well as the calibration of Forata and Bellus. Enhancing the model performance in all these points, apart from Forata and Bellus, would require more data and a detailed representation of these flows. Furthermore, the impact of Forata and Bellus in the overall system performance is limited and would not justify the time spent in improving their calibration.

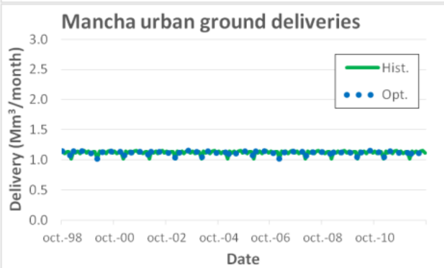
A2.3. RESULTS

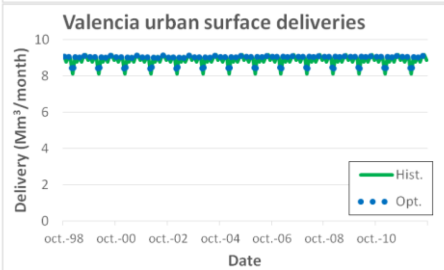
A2.3.1. Urban demands

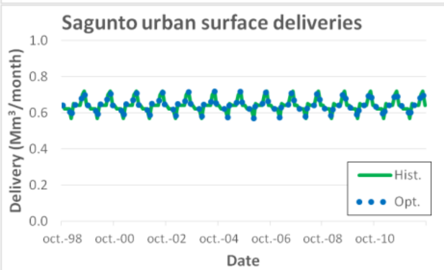
	Category	**Consumptive uses**			
	Type	Urban			
	Variable (1998-2011 period)	Albacete	Mancha	Valencia	Sagunto
Current operation	Surface deliveries (Mm³/year)	14.33	0.00	106.81	7.70
	Groundwater deliveries (Mm³/year)	2.69	13.41	0.00	0.00
	Economic benefits (M€/year)	34.18	26.08	213.32	15.46
Optimal decisions	Surface deliveries (Mm³/year)	13.64	0.00	106.81	7.70
	Groundwater deliveries (Mm³/year)	3.38	13.41	0.00	0.00
	Economic benefits (M€/year)	34.26	26.10	213.32	15.46
Difference	Surface deliveries (Mm³/year)	-0.70	0.00	0.00	0.00
	Groundwater deliveries (Mm³/year)	0.70	0.00	0.00	0.00
	Economic benefits (M€/year)	0.08	0.02	0.00	0.00







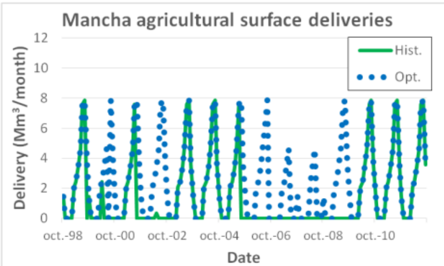


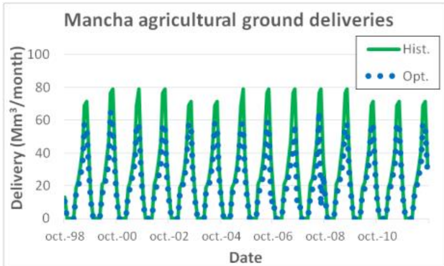


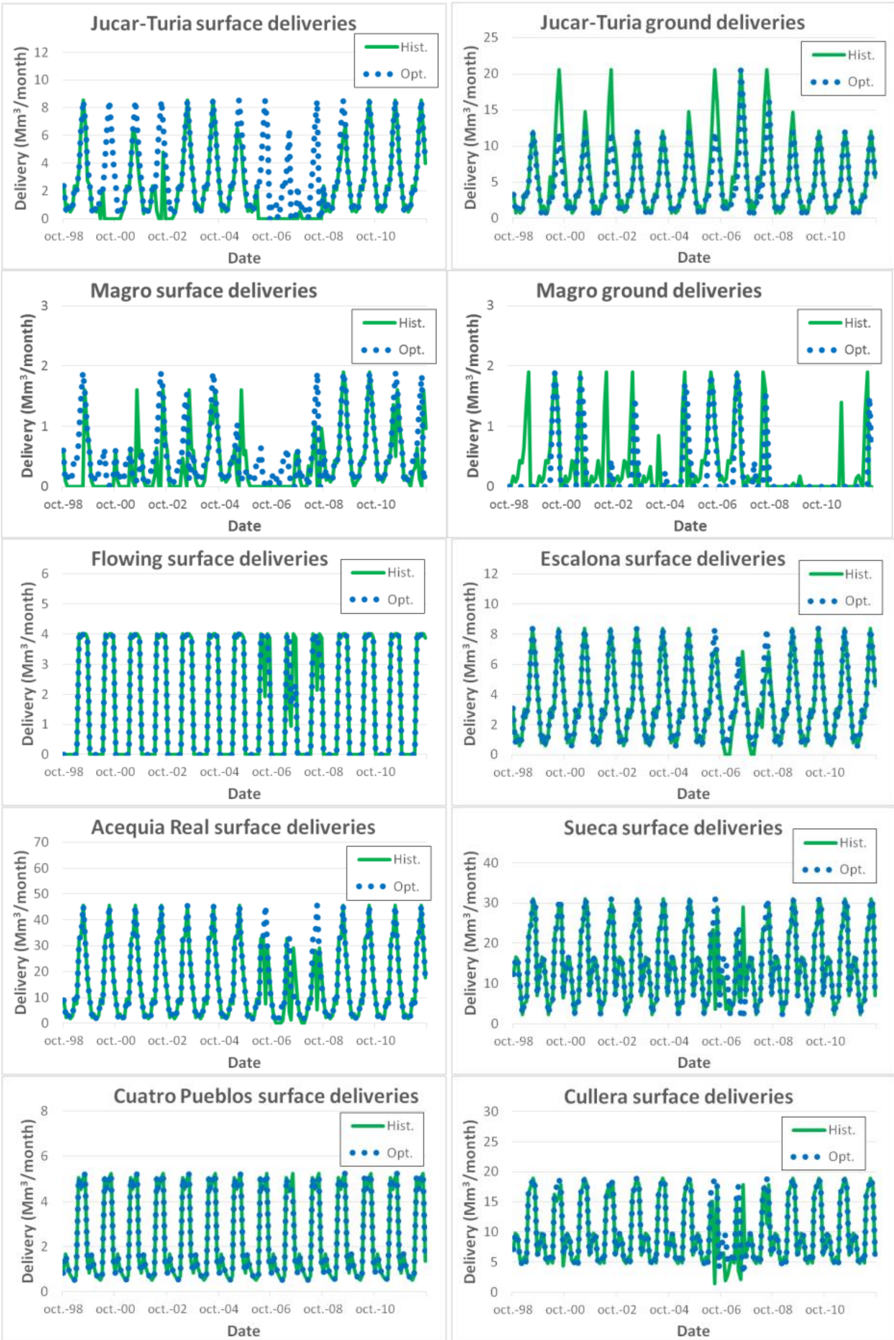
A2.3.2. Agricultural demands

	Category	Consumptive uses								
	Type	Agricultural[1]								
	Variable (1998-2011 period)	Mancha	Jucar-Turia	Magro	Flowing	Escalona	Ac. Real	Sueca	Cuatro Pueblos	Cullera
Current operation	Surface deliveries (Mm³/year)	16.96	25.19	4.30	19.13	40.71	181.31	173.61	27.34	117.62
	Groundwater deliveries (Mm³/year)	315.45	69.00	4.10	0.00	0.00	0.00	0.00	0.00	0.00
	Economic benefits (M€/year)	78.89	47.34	4.31	5.82	12.39	33.97	4.18	2.12	10.71
Optimal decisions	Surface deliveries (Mm³/year)	29.13	36.27	5.86	19.13	41.24	189.60	176.95	27.26	121.69
	Groundwater deliveries (Mm³/year)	238.30	57.47	2.52	0.00	0.00	0.00	0.00	0.00	0.00
	Economic benefits (M€/year)	78.34	47.83	4.38	5.85	12.51	35.42	4.43	2.12	11.35
Difference	Surface deliveries (Mm³/year)	12.17	11.08	1.56	0.00	0.52	8.28	3.34	-0.09	4.07
	Groundwater deliveries (Mm³/year)	-77.14	-11.53	-1.58	0.00	0.00	0.00	0.00	0.00	0.00
	Economic benefits (M€/year)	-0.55	0.49	0.07	0.03	0.12	1.45	0.25	-0.01	0.64

[1]: not including the economic benefits of rice demands

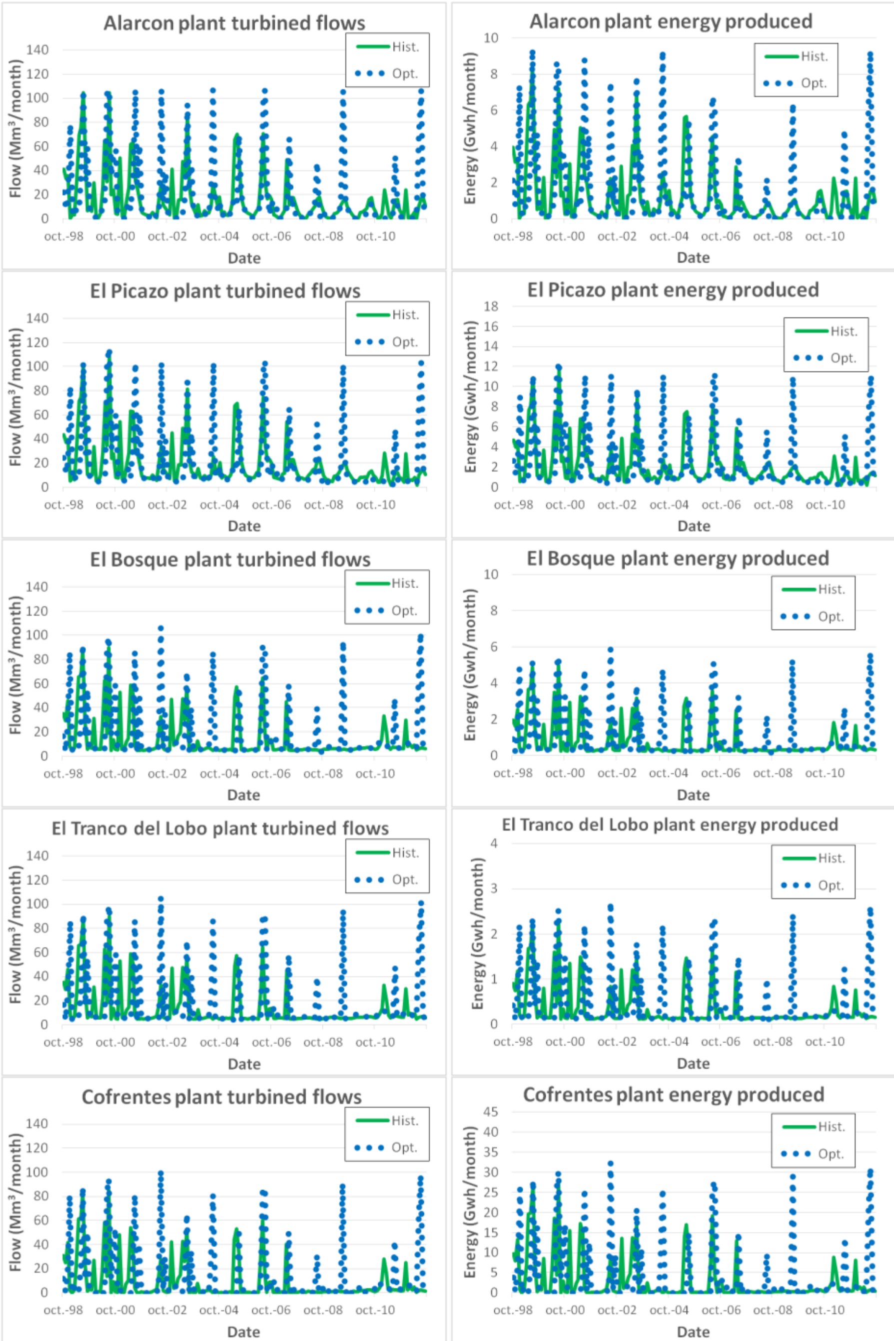


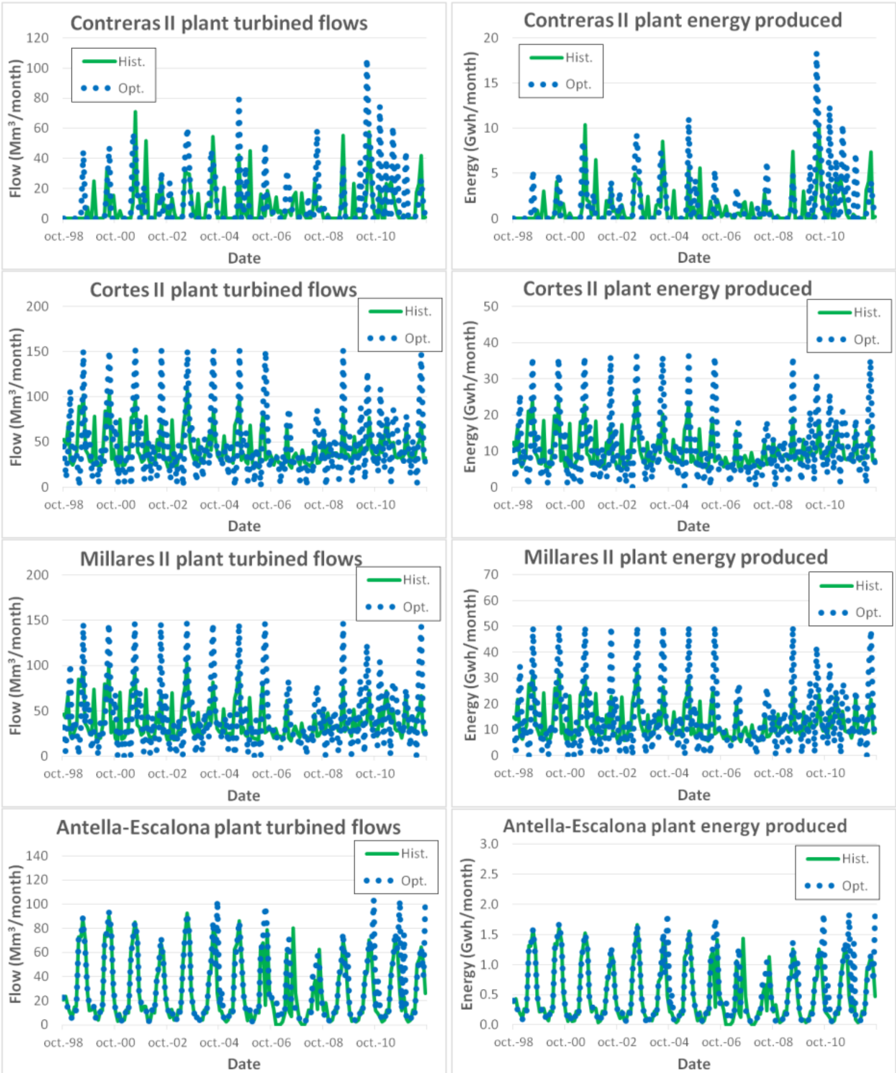



Jucar-Turia surface deliveries
Jucar-Turia ground deliveries
Magro surface deliveries
Magro ground deliveries
Flowing surface deliveries
Escalona surface deliveries
Acequia Real surface deliveries
Sueca surface deliveries
Cuatro Pueblos surface deliveries
Cullera surface deliveries
Hist.
Opt.
Delivery (Mm³/month)
Date
oct.-98
oct.-00
oct.-02
oct.-04
oct.-06
oct.-08
oct.-10

A2.3.3. Hydropower plants

	Category	Energy production								
	Type	Hydropower								
	Variable	Alarcon	El Picazo	El Bosque	El Tranco del Lobo	Cofrentes	Contreras II	Cortes II	Millares II	Antella - Escalona
Current operation	Turbined flow (Mm^3/year)	186.50	223.60	160.29	160.29	104.68	94.31	509.46	455.31	325.55
	Energy produced (GWh/year)	14.34	24.16	8.91	4.09	33.49	13.47	119.26	148.64	5.85
	Economic benefits (M€/year)	0.83	1.45	0.53	0.24	2.01	0.81	7.14	8.91	0.35
	Water use intensity (m^3/Kwh)	13.01	9.26	17.99	39.18	3.13	7.00	4.27	3.06	55.66
	Water use productivity (€/m^3)	0.004	0.006	0.003	0.002	0.019	0.009	0.014	0.020	0.001
Optimal decisions	Turbined flow (Mm^3/year)	196.11	219.78	189.87	189.87	134.31	111.96	550.17	495.27	366.37
	Energy produced (GWh/year)	14.90	23.75	10.56	4.85	42.52	16.06	127.20	167.62	6.58
	Economic benefits (M€/year)	0.88	1.43	0.64	0.29	2.58	0.97	7.68	10.13	0.39
	Water use intensity (m^3/Kwh)	13.17	9.26	17.99	39.18	3.16	6.97	4.33	2.95	55.66
	Water use productivity (€/m^3)	0.004	0.007	0.003	0.002	0.019	0.009	0.014	0.020	0.001
Difference	Turbined flow (Mm^3/year)	9.61	-3.82	29.58	29.58	29.63	17.65	40.70	39.96	40.82
	Energy produced (GWh/year)	0.56	-0.41	1.64	0.76	9.03	2.59	7.94	18.99	0.73
	Economic benefits (M€/year)	0.05	-0.01	0.10	0.05	0.58	0.16	0.54	1.22	0.04
	Water use intensity (m^3/Kwh)	0.16	0.00	0.00	0.00	0.03	-0.03	0.05	-0.11	0.00
	Water use productivity (€/m^3)	0.000	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000


Alarcon plant turbined flows
Flow (Mm³/month)
Hist.
Opt.
Date
Alarcon plant energy produced
Energy (Gwh/month)
Hist.
Opt.
Date
El Picazo plant turbined flows
Flow (Mm³/month)
Hist.
Opt.
Date
El Picazo plant energy produced
Energy (Gwh/month)
Hist.
Opt.
Date
El Bosque plant turbined flows
Flow (Mm³/month)
Hist.
Opt.
Date
El Bosque plant energy produced
Energy (Gwh/month)
Hist.
Opt.
Date
El Tranco del Lobo plant turbined flows
Flow (Mm³/month)
Hist.
Opt.
Date
El Tranco del Lobo plant energy produced
Energy (Gwh/month)
Hist.
Opt.
Date
Cofrentes plant turbined flows
Flow (Mm³/month)
Hist.
Opt.
Date
Cofrentes plant energy produced
Energy (Gwh/month)
Hist.
Opt.
Date
oct.-98 oct.-00 oct.-02 oct.-04 oct.-06 oct.-08 oct.-10



Contreras II plant turbined flows
Flow (Mm³/month)
0 20 40 60 80 100 120
Hist.
Opt.
oct.-98 oct.-00 oct.-02 oct.-04 oct.-06 oct.-08 oct.-10
Date
Contreras II plant energy produced
Energy (Gwh/month)
0 5 10 15 20
Hist.
Opt.
oct.-98 oct.-00 oct.-02 oct.-04 oct.-06 oct.-08 oct.-10
Date
Cortes II plant turbined flows
Flow (Mm³/month)
0 50 100 150 200
Hist.
Opt.
oct.-98 oct.-00 oct.-02 oct.-04 oct.-06 oct.-08 oct.-10
Date
Cortes II plant energy produced
Energy (Gwh/month)
0 10 20 30 40 50
Hist.
Opt.
oct.-98 oct.-00 oct.-02 oct.-04 oct.-06 oct.-08 oct.-10
Date
Millares II plant turbined flows
Flow (Mm³/month)
0 50 100 150 200
Hist.
Opt.
oct.-98 oct.-00 oct.-02 oct.-04 oct.-06 oct.-08 oct.-10
Date
Millares II plant energy produced
Energy (Gwh/month)
0 10 20 30 40 50 60 70
Hist.
Opt.
oct.-98 oct.-00 oct.-02 oct.-04 oct.-06 oct.-08 oct.-10
Date
Antella-Escalona plant turbined flows
Flow (Mm³/month)
0 20 40 60 80 100 120 140
Hist.
Opt.
oct.-98 oct.-00 oct.-02 oct.-04 oct.-06 oct.-08 oct.-10
Date
Antella-Escalona plant energy produced
Energy (Gwh/month)
0.0 0.5 1.0 1.5 2.0 2.5 3.0
Hist.
Opt.
oct.-98 oct.-00 oct.-02 oct.-04 oct.-06 oct.-08 oct.-10
Date

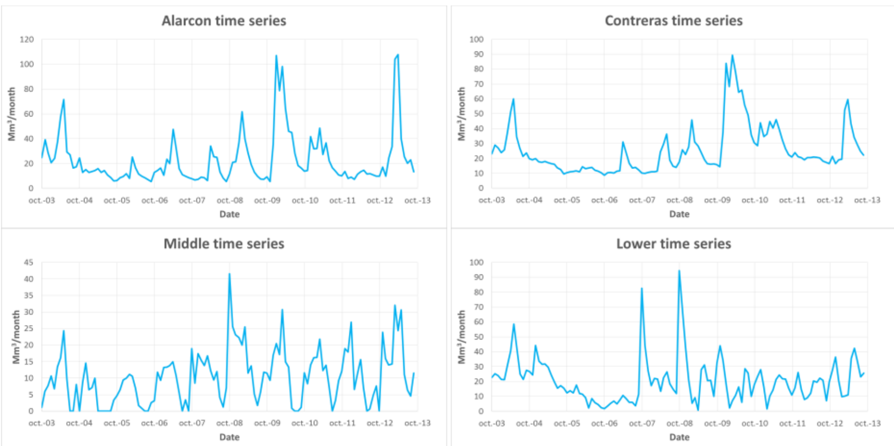
A3. JUCAR SEASONAL OPERATION MODEL

A3.1. DESCRIPTION

A3.1.1. Inflows

The inflow data used by the seasonal operation model was calculated from the information provided by the Operation Office and from CHJ (2013). This information consisted of inflows, outflows and storages for each reservoir, as well as the discharge from the sub-basins located downstream of the Tous reservoir. Storages and outflows were obtained by direct measurement at the dams, while inflows to the reservoirs and the discharge downstream Tous were calculated by performing water balances. The inflows used in the model were estimated as:

- Alarcon sub-basin: inflows to Alarcon provided by the Operation Office plus evaporation losses.
- Contreras sub-basin: inflows to Contreras provided by the Operation Office plus evaporation and seepage losses.
- Middle sub-basin: inflows to Tous provided by the Operation Office plus evaporation and seepage losses minus Alarcon and Contreras releases and Hoces del Cabriel aquifer discharge.
- Lower sub-basin: inflow time series provided by the Operation Office.



Seasonal operation model inflows

Although the inflow records available span from October 1998 to September 2013, the final analysis period selected spans from October 2003 to September 2013. This guarantees a steady framework for the system operation, since the Alarcon Agreement was signed in 2001.

A3.1.2. Reservoirs

The decision-making processes in the Jucar river system take explicitly into account Alarcon, Contreras and Tous. The remaining facilities are devoted exclusively to hydropower (Molinar, Cortes II and Naranjero) or are not large enough to play a basinwide role in seasonal management (Forata and Bellus). Consequently, only Alarcon, Contreras and Tous were considered, with the same features as the conjunctive use model.

A3.1.3. Aquifers and stream-aquifer interaction

In spite of the stream-aquifer interactions noticed, groundwater bodies are not taken into account in the seasonal operation of the Jucar river system. On the contrary, groundwater management is addressed by the long-term planning. Therefore, no stream-aquifer interactions were necessary in the seasonal operation model. The stream-aquifer interaction shared between the Jucar river and the Mancha Oriental aquifer was not explicitly modeled, but added to the middle sub-basin inflows. The only stream-aquifer interaction required is the one between the Cabriel river and the Hoces del Cabriel aquifer. Since the latter is recharged by the seepage losses from Contreras, a change in the reservoir operation affects the stream-aquifer interaction. The stream-aquifer interaction has been modeled using an EMM whose parameters were defined as done in CHJ (2013).

A3.1.4. Canals

The same canals included in the conjunctive use model were considered in the seasonal operation one. The differences between the type of elements used to model them (stream and intake) regards to modeling choices that do not affect the way in which water is distributed.

A3.1.5. Environmental flows

Besides the minimum flows established downstream Alarcon and Contreras, the model takes into account the minimum flow rates through the Antella weir (the Acequia Real intake location), the Sueca weir (the Sueca irrigation demand intake location), the Cullera weir (the Cullera irrigation demand intake location) and the Marquesa weir (outflows to the Jucar mouth in the Mediterranean Sea). The rest of the minimum environmental flows have not been included due to modeling decisions. Anyway, the fulfillment of all the minimum flows in river streams that have an equivalent in the seasonal operation model has been checked.

The Jucar minimum flow downstream Alarcon do not correspond to the minimum flow required to be released through the dam (which can be diverted to the Tajo-Segura canal and to the river); but to the minimum flow downstream the Molinar reservoir, in order to reproduce the flows at the end of the modeled stream.

Seasonal operation model monthly environmental flows (m^3/s)

Location	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Jucar in Alarcon	2.00	2.00	2.00	2.40	2.40	2.40	2.40	2.40	2.00	2.00	2.00	2.00
Cabriel in Contreras	0.80	0.80	0.80	0.96	0.96	0.96	0.96	0.96	0.80	0.80	0.80	0.80
Jucar in Antella	1.80	1.80	1.80	2.16	2.16	1.80	1.80	1.80	1.80	1.80	1.80	1.80
Sueca weir	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50	1.50
Marquesa weir	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.50

A3.1.6. Demands

Two different types of demands have been considered: urban and agricultural. No industrial demands were taken into account due to:

- The Cofrentes nuclear power plant demand must be always satisfied due to strategic reasons, so no decision is made with regard to it. Its effect has been already taken into account in the middle sub-basin inflows, which lumps all the water flows of the middle Jucar.
- Neither the Reservoir Releases Commission nor the Operation Office decide on hydropower generation. Due to that, no hydropower plant has been taken into account.

A3.1.6.1. Urban demands

The urban demands considered were the Albacete, Valencia and Sagunto municipalities. The rest of the system demands are supplied using groundwater, so they have not been taken into account. The monthly values have been obtained from the data provided by the CHJ Operation Office (2003-2013 period) for the Jucar-Turia canal (which supplies the cities of Valencia and Sagunto, as well as the Jucar-Turia agricultural demand) and for the Tajo-Segura canal (which supplies the Albacete city, as well as the part of the Mancha Oriental demand whose source was switched from groundwater to surface water). This information has been compared and contrasted with the one from CHJ (2013)

Seasonal operation model monthly urban demands (Mm^3)

Demand	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Albacete	1.44	1.39	1.44	1.44	1.30	1.44	1.39	1.44	1.39	1.44	1.45	1.39
Valencia	7.26	7.01	7.18	7.18	6.50	7.26	7.01	7.26	7.01	7.26	7.34	7.01
Sagunto	0.51	0.50	0.50	0.50	0.46	0.52	0.51	0.51	0.51	0.56	0.58	0.51

A3.1.6.2. Agricultural demands

No separation was assumed between citrus and rice, since no economic calculations are going to be made. Since only surface agricultural demands have been considered, the vast majority of the agricultural water use is located downstream Tous. Monthly agricultural amounts have been obtained from the data provided by the CHJ Operation Office, from 2003 to 2013, for the Tajo-Segura canal, the Jucar-Turia canal and the main irrigation canals or *acequias* (Acequia Real, Escalona, Cuatro Pueblos, Sueca and Cullera). Each canal has been considered as a single demand. In addition, the CHJ Operation Office acknowledges the existence of small agricultural demands located besides the Jucar river bed, which abstract water directly from it. These demands use, according to the Operation Office, around 1.5 m^3/s during the irrigation season.

Seasonal operation model monthly agricultural demands (Mm^3)

Demand	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Jucar-Turia	2.46	1.31	0.51	0.68	1.00	0.99	1.80	3.66	6.52	8.56	6.76	4.00
Acequia Real	8.70	6.99	1.45	3.89	6.48	6.12	10.15	37.98	39.79	42.44	41.12	32.15
Escalona	1.91	1.00	0.24	0.57	0.66	0.79	1.32	2.94	6.20	7.87	7.60	5.20
Sueca	12.12	16.36	15.71	9.51	2.25	4.84	5.37	26.24	29.31	38.01	36.20	6.89

Demand	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Cuatro Pueblos	0.43	1.39	0.58	0.50	0.14	0.32	0.66	4.49	4.15	5.21	5.34	2.71
Cullera	5.94	8.36	7.75	4.49	2.64	3.77	4.46	16.92	17.31	19.66	19.24	9.77
Mancha Oriental agricultural surface	1.45	0.00	0.00	0.00	0.00	2.08	2.44	3.40	4.62	7.59	7.85	3.56
Flowing	0.00	0.00	0.00	0.00	0.00	0.00	0.00	4.02	3.89	4.02	4.02	3.89

No agricultural returns to the Jucar river have been considered. They have been dismissed because the lower sub-basin inflows, calculated using a water balance, already take them into account. Furthermore, representing them would depart from the current practices of the CHJ Operation Office, which does not taken them into account in decision-making.

A3.1.7. Priorities

In the seasonal operation model, demand priorities have been used in both the optimization and the simulation runs. In the first, they guide the optimal decisions made by the model in order to maximize the amount of water allocated according to the CHJ Operation Office's goals. In the latter, priorities mimic the current observed behavior and water right prevalence.

Seasonal operation model monthly demand priorities

Location	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep
Valencia	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Sagunto	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Jucar-Turia	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100	1100
Acequia Real	650	650	650	650	650	650	650	1500	1500	1500	1500	1500
Escalona	650	650	650	650	650	650	650	1500	1500	1500	1500	1500
Sueca	650	650	650	650	650	650	650	1500	1500	1500	1500	1500
Cuatro Pueblos	650	650	650	650	650	650	650	1500	1500	1500	1500	1500
Cullera	650	650	650	650	650	650	650	1500	1500	1500	1500	1500
Albacete	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000	2000
Mancha Oriental agriculture	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000	1000
Flowing	0	0	0	0	0	0	0	1800	1800	1800	1800	1800

The highest priority corresponds to the urban water uses, according to the Spanish legal framework. Among the agricultural users, the highest priority is given to the Flowing demand, since it abstracts water directly from the river. The lowest priority among the agricultural demands is given to the Jucar-Turia and the Mancha Oriental, which do not have elder rights. However, out of the irrigation season (from October to April) the situation inverts because water availability is higher and less resource is required in the downstream demands, being also more flexible to deficits. On the other hand, the Mancha Oriental and the Jucar-Turia demands implement crop mosaics differing from the downstream ones, being more sensitive to deficits between October and April.

A3.1.8. Specific constraints

The main constraint considered by the seasonal operation model is the Alarcon Agreement, explained in section 5.2. It has been added through a storage limit in the Alarcon reservoir. If the storage is below the limit, no delivery is made to the Jucar-Turia and the Mancha Oriental agricultural demands.

Although not affecting the reservoir releases, one important factor regarding deliveries is the existence of emergency wells. These have an impact on how the surface resource is allocated during drought periods due to its asymmetric distribution. The irrigation districts with higher concentrations of emergency wells (Acequia Real and Sueca, CHJ 2013) support the highest deficit of surface waters during water scarcity periods, replacing them with the emergency wells. Constraints have been added to represented this assymetric deficit distribution.

A3.1.9. Stochastic models

An ARMA (1,1) model has been chosen to generate openings and time series, while an MPAR (1) model has been employed to estimate the cuts' parameters associated with the inflows. In this case, the number of data records per parameter is 3.33, way below the 6 threshold value (Salas et al., 1980). A set of 20 openings and two sets of 20 times series were generated. The first time series set has been used in the CSG-SDDP run, while the second has been employed to compare the current operating rules with the optimal ones.

The MPAR (1) parameters correspond to:

$\delta_{1,oct}$	Alarcon	Contreras	Middle	Lower
Alarcon	0.40	-0.58	-0.26	0.64
Contreras	0.35	0.01	0.46	-0.02
Middle	-0.62	0.64	0.65	-0.48
Lower	-1.55	1.17	0.35	0.33

$\delta_{1,apr}$	Alarcon	Contreras	Middle	Lower
Alarcon	1.44	-0.74	0.15	0.26
Contreras	0.31	0.64	0.05	0.13
Middle	0.74	-0.46	0.21	-0.19
Lower	0.48	0.33	-0.74	0.79

$\delta_{1,nov}$	Alarcon	Contreras	Middle	Lower
Alarcon	0.71	0.04	0.32	-0.19
Contreras	0.22	0.76	0.35	-0.14
Middle	-0.11	0.00	0.66	-0.27
Lower	-0.08	0.22	0.01	0.92

$\delta_{1,may}$	Alarcon	Contreras	Middle	Lower
Alarcon	-0.20	0.61	0.43	0.56
Contreras	-0.45	1.10	0.25	0.28
Middle	0.40	0.02	0.57	0.21
Lower	0.03	0.00	0.46	0.74

$\delta_{1,dec}$	Alarcon	Contreras	Middle	Lower
Alarcon	-0.26	0.77	-0.61	0.28
Contreras	-0.62	1.15	-0.52	0.20
Middle	-0.57	0.33	0.42	0.55
Lower	-0.37	0.58	0.06	0.56

$\delta_{1,jun}$	Alarcon	Contreras	Middle	Lower
Alarcon	-0.22	1.25	-0.12	-0.12
Contreras	-0.71	1.63	-0.07	-0.15
Middle	0.41	-0.51	0.73	0.02
Lower	-0.59	-0.07	0.57	0.91

$\delta_{1,jan}$	Alarcon	Contreras	Middle	Lower
Alarcon	0.72	-0.07	0.36	-0.01
Contreras	0.37	0.38	0.28	-0.05
Middle	-0.66	1.04	1.12	-0.90
Lower	-0.20	-0.11	-0.81	1.39

$\delta_{1,jul}$	Alarcon	Contreras	Middle	Lower
Alarcon	1.31	-0.37	-0.26	0.37
Contreras	0.03	0.98	-0.30	0.15
Middle	-0.45	0.42	0.53	0.23
Lower	-0.23	0.95	-0.42	0.90

$\delta_{1,feb}$	Alarcon	Contreras	Middle	Lower
Alarcon	2.26	-1.47	0.23	0.12
Contreras	0.72	0.14	0.24	0.17
Middle	3.18	-2.82	0.30	-0.09
Lower	-0.72	0.40	-0.31	0.56

$\delta_{1,aug}$	Alarcon	Contreras	Middle	Lower
Alarcon	0.59	0.09	0.27	0.20
Contreras	-0.10	1.10	-0.01	-0.04
Middle	-0.99	0.03	-0.02	0.88
Lower	-0.35	0.03	-0.44	1.37

$\delta_{1,mar}$	Alarcon	Contreras	Middle	Lower
Alarcon	1.36	-0.58	-0.30	-0.18
Contreras	0.55	0.46	-0.30	-0.11
Middle	0.86	-0.32	0.30	-0.03
Lower	-0.08	0.30	-0.11	0.96

$\delta_{1,sep}$	Alarcon	Contreras	Middle	Lower
Alarcon	0.63	0.22	-0.13	0.11
Contreras	0.14	0.77	0.01	0.14
Middle	0.25	-0.75	0.34	0.83
Lower	1.07	-0.91	-0.26	0.41

The ARMA (1,1) parameters correspond to:

δ_1	Alarcon	Contreras	Middle	Lower
Alarcon	0.79	0.00	0.02	0.10
Contreras	-0.05	0.92	0.05	0.05
Middle	-0.02	-0.03	0.84	0.03
Lower	-0.07	0.15	-0.08	0.60

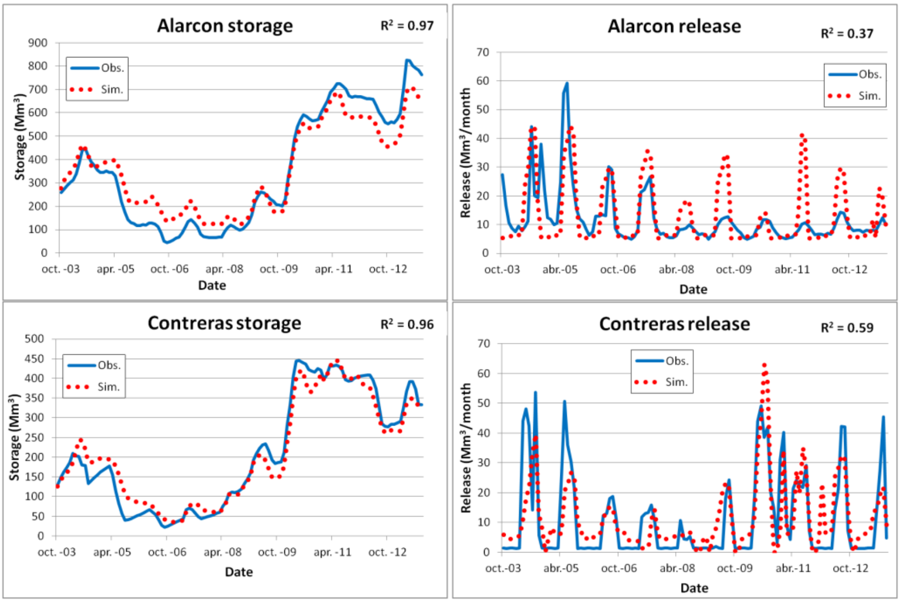
ω_1	Alarcon	Contreras	Middle	Lower
Alarcon	0.10	-0.21	0.05	0.04
Contreras	0.02	-0.04	0.07	0.01
Middle	-0.03	-0.06	0.39	-0.02
Lower	0.00	-0.06	0.00	-0.12

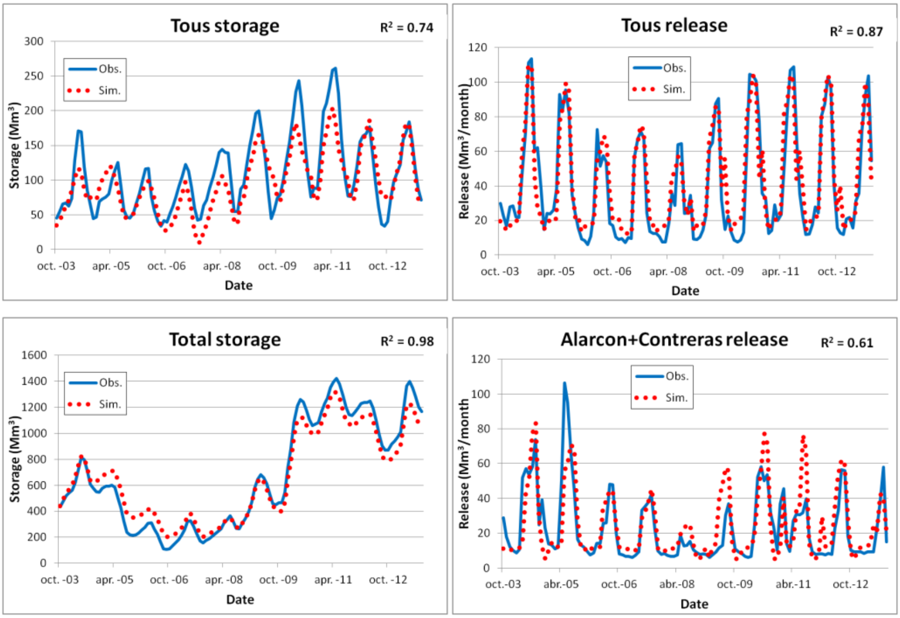
ω_0	Alarcon	Contreras	Middle	Lower
Alarcon	0.61	0.00	0.00	0.00
Contreras	0.31	0.26	0.00	0.00
Middle	0.11	0.19	0.76	0.00
Lower	-0.04	0.08	0.15	0.67

A3.2. VALIDATION

A3.2.1. Reservoir storages and releases

The validation of storages is good, with an average R-squared coefficient of 0.91 (0.97, 0.96, 0.74 and 0.98). The validation for the Alarcon and Contreras releases is better considering them jointly (R-squared equal to 0.61) than in isolation (0.37 and 0.56 respectively). The reproduction of the summer releases in Contreras is better than the Alarcon ones, although the other way round is found when moving out of the irrigation season.





These differences can be explained by the fact that the FRB systems represent an *ex ante* situation, while the historical records correspond to the *ex post* one. The difference between both is that the CHJ Operation Office monitors the releases and adjusts them, if necessary, on a daily basis. These updates of the operation decisions are not accounted by the model. They are especially sensitive to the inflows to Alarcon and Contreras, not taken into account in the *ex ante* evaluation. This issue explains why the joint releases offer a better adjustment than comparing them in isolation.

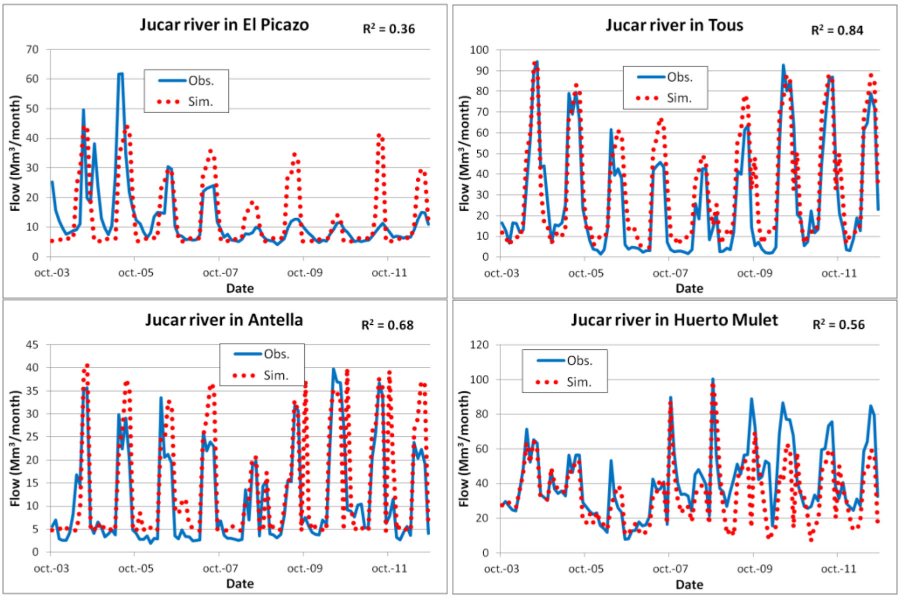
The releases from Tous offer a close reproduction of the historical ones (R-squared of 0.81), without a noticeable effect of the difference between the *ex ante* and the *ex post* evaluation. This is caused by two facts:

- Historical records, which depict an *ex post* situation, were the main driver of the delivery FRB determining the Tous releases.
- The releases from Tous, rather than a variable, are perceived as a commitment, so the CHJ Operation Office tries to guarantee them unless exceptional conditions are found.

Considering that the releases from Tous, which are the most important, are well reproduced by the model, as well as the good reproduction of the storage levels, it has been considered that the model is adequately reproducing the historical performance of the system.

A3.2.2. Streamflows

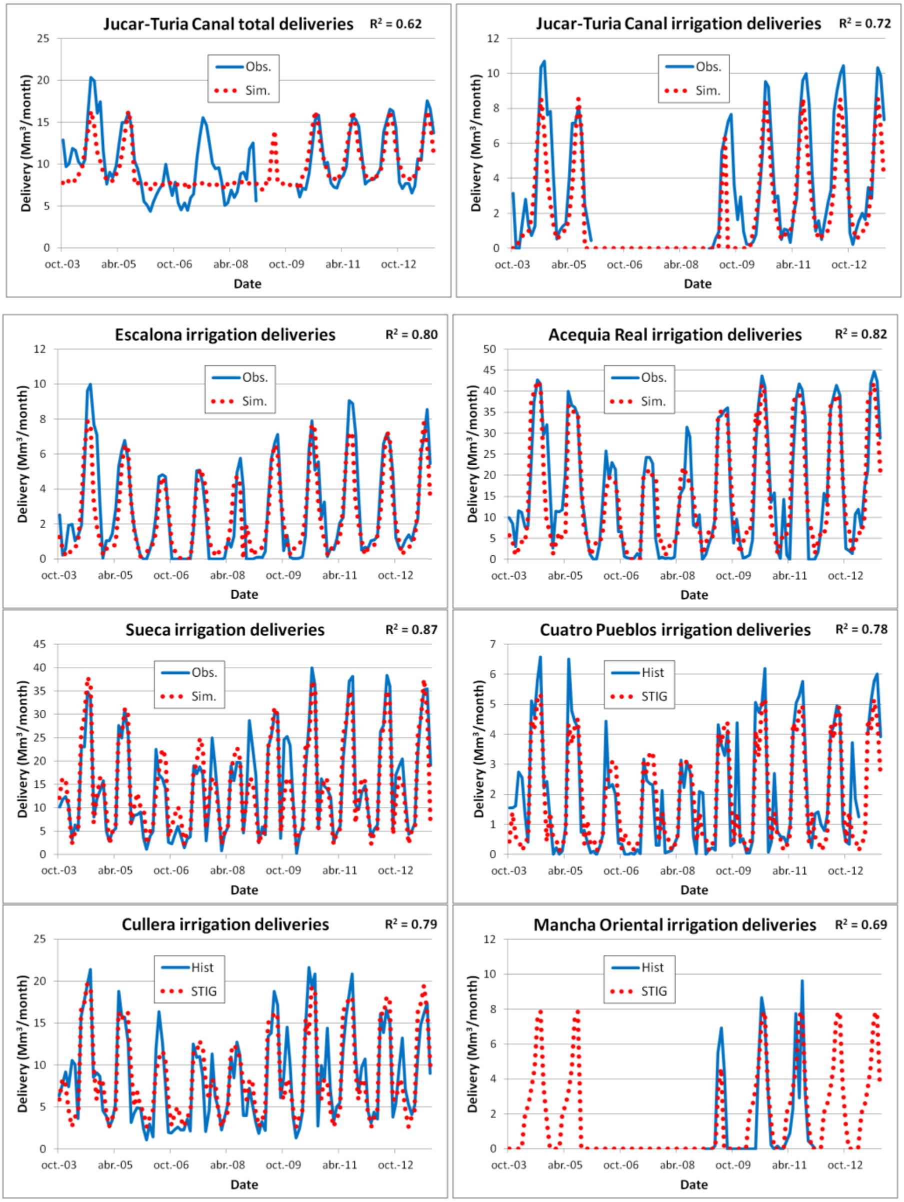
Some gauging stations in the Jucar river basin have been used to validate the FRB systems. In the middle streams of the system, the validation done at El Picazo (Jucar river, R-squared 0.36) is not good, since it is affected by the same issues pointed out for the Alarcon release. The reproduction of the middle Jucar is worse than the lower one, since it is not modeled in detail. The validation for the lower sub-basin (downstream of Tous) gauging stations is better, with an average R-squared value of 0.70 (0.84 in Tous, 0.68 in Antella and 0.56 in Huerto de Mulet). The Huerto de Mulet records are affected by the Sueca weir.

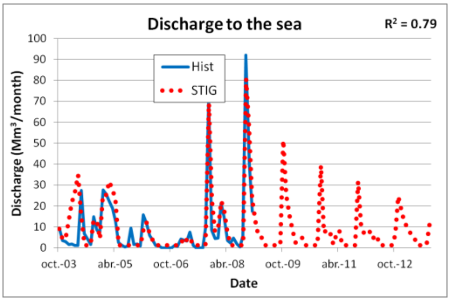


A3.2.3. Demand deliveries

Regarding the deliveries and the sea outflows, almost all the demands included in the seasonal operation model have historical records to validate them (with the exception of Albacete and the flowing demands). An average R-squared value of 0.76 has been found, ranging from 0.62 to 0.87.

The hedging experienced by the demands is fairly reproduced by the model, as well as the historical periods in which no surface water was allocated to the Mancha Oriental and Jucar-Turia agricultural districts. Furthermore, the sea outflows are properly reproduced by the model, one key aspect since it directly impacts the water resources that can be devoted to agricultural purposes in the lower Jucar.





A3.2.4. Summary

On a broader view, the Jucar river system seasonal operation model seems to be valid, so the operating rules represented by the FRB systems offer a quite reasonable approximation of its historical performance. The storages in the three reservoirs is adequately reproduced, although some deviations regarding the balance between the Alarcon and Contreras releases has been found.

The validation of the model for the lower basin (downstream Tous) has been good for both streamflows and deliveries, with no R-squared coefficient lower than 0.56. The surface deliveries to the demands reproduce the in-year pattern, the hedging and the time stages in which no supply was made to the Jucar-Turia and the Mancha Oriental agricultural demands due to the Alarcon Agreement. Consequently, it can be assumed that the model represents in a proper way the reservoir operation and the demand-meeting strategies followed by the CHJ Reservoir Releases Commission and the CHJ Operation Office.

The clear improvement of the model is the balance between the Alarcon and Contreras releases. However, it does not have significant impacts on the long-term storage levels. Although the representation of the middle Jucar is also not good due to the lack of detail, the CHJ Operation Office focus is on the downstream part of the system, so no improvement in this area is necessary so far.