DISCOVERING RESERVOIR MANAGEMENT CRITERIA: THE CASE STUDY OF POZZILLO RESERVOIR [1]

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Abstract: An integrated Rough Set approach is proposed to discover the historical operation rules of irrigation purpose reservoirs. Operation rules are derived by expressing monthly releases as functions of reservoir stored volume, inflow and outflow. This is accomplished through the Rough Set approach and the use of performance indices able to recognize the effective rules used in water supply management. This approach represents a new mathematical tool quite different to classical fuzzy rule-based systems in the decision rules induction. Results show that the integrated Rough Set approach allows to individuate with acceptable reliability the real criteria used for the system management.

Keywords: Decision support systems, Logical control, Management systems, Multiple criterion optimisation, Regulation, Rules

1. INTRODUCTION

A better satisfaction of water needs in agriculture includes issues such as: (a) increasing storage capacities; (b) improving irrigation conveyance and distribution systems; (c) enhancing operation of water supply systems; (d) development of new sources of water supplies (Pereira *et al.*, 2002). In regions, such as Sicily, suffering from frequent water shortages, the operation of irrigation water supply systems could be enhanced by the definition of efficient reservoir operating rules. Presently these rules are often inaccurate, due to the difficulties in the evaluation of controlling factors such as the inter-intra seasonal variability of rainfall-runoff processes and crop water requirements. Incorporation of decision support tools into reservoir management could reduce the risk of failure for the system to achieve its prescribed goals. This places the focus on new-generation techniques and tools emerging to intelligently assist humans in analyzing data, finding useful knowledge and in some cases performing analysis automatically (Bhatty, 1991; An *et al.*, 1996; Raman and Chandramoui, 1997; Rossi *et al.*, 1999; Barbagallo *et al.*, 2001, 2003). Using such techniques, the defini-

[1] Work carried out with equivalent contributions of the Authors. Project AQUATEC "Tecnologie Innovative di Controllo, Trattamento e Manutenzione per la Soluzione dell'Emergenza Acqua" funded by the Italian Ministry of Education, Research and Technological Development (PON 2000-2006).

tion of reservoir operating rules has been generally pursued by expressing the series of releases as function of reservoir state variables (storage volume), hydrological input (inflow) and operational features (outflow) (Young, 1967). Bhaskar and Whitlatch (1980) tested linear as well as nonlinear monthly operating rules by regressing the series of releases with reservoir storage at the beginning of each month and previous month-current inflow. Karamouz and Houck (1987), Barbagallo *et al.* (2001; 2003) investigated the release policies of single-purpose reservoirs using the operation and system-state characteristics (release, stored volume, inflow) which precede in time the release for the time period t. Stam *et al.* (1998) analyzed reservoir release strategy involving evaluation on how the reservoir storage evolve over twelve months. Rossi *et al.* (1999) used a neural network approach to determine monthly optimal releases from a reservoir as function of available information on stored volume and release in the previous month.

The Rough Set theory (Pawlak, 1982) is a new tool for discovering relationships hidden in data and express them in the natural language of decision rules. In the last years the Rough Set theory has been applied in multi-criteria decision analysis, allowing the recognition of relationships between control variables (Slowinski, 1993; Pawlak and Slowinski, 1994); relevant applications of the Rough Set theory cover fields of medicine, pharmacology, engineering, banking, finances, market analysis and environmental management (Pawlak, 1997; 2002). Very few applications of the Rough Set theory focused aspects of water resources planning and management (An *et al.*, 1996; Chen *et al.*, 2003) regarding the identification of optimal control strategies for immediate future time period and the discovery of historical rules for water systems management. System performance optimization problems were investigated by Chen *et al.* (2003) who have proposed an innovative approach to integrate the indiscernibility of the Rough Set theory with neural-fuzzy theory to control and optimize wastewater treatment processes in terms of operating cost, control stability and response in time. An *et al.* (1996) proposed an enhanced Rough Set approach for generating prediction rules from a set of observed data to analize water distribution system processes; in their work the Authors investigate real systems management criteria to suggest possible solutions by adopting optimal control criteria. Following the latter approach, the work herein presented aims to set up a methodology based on a Rough Set approach for the analysis of historical data and the discovery of practiced operating rules of an irrigation-purpose reservoir. The paper is organized into five sections. Following the introduction, the second section illustrates the Rough Set theory. The third section describes the methodology of implementation of an integrated Rough Set approach to an irrigation reservoir as a case study. The fourth section reports the results of the case-study implementation of the integrated Rough Set approach. The last section summarises the most important findings.

2. THE ROUGH SET THEORY

The Rough Set theory introduced by Pawlak (1982) is a mathematical approach to deal with a specific type of uncertainty in data related to granulation of the information, i.e. situations in which objects having equal description are assigned to different classes. This type of uncertainty is very different from the uncertainty considered within the Fuzzy Set theory (Zadeh, 1965; see also Dubois and Prade, 1980) which deals with a type of imprecision arising when the boundaries of a class of objects are not sharply defined. Informally, a fuzzy set may be regarded as a class in which there is a graduality of progression from membership to non-membership or, more precisely, in which an object may have a grade of membership intermediate between unity (full membership) and zero (non-membership). Since the type of uncertainty considered by rough set and fuzzy set is so different, the two theories appear as complementary rather than competitive as acknowledged by a large number of studies (see e.g. Pawlak, 1985; Dubois and Prade, 1990; Greco *et al.*, 2000). In the field of water management, many applications of the fuzzy set methodology are proposed (Shrestha, 1996; Fontane *et al.*, 1997; Labadie, 2004). Some of these applications try to define decision rules. Anyway, the approach to decision rules induction is quite different from that of Rough Set theory. The main difference between Fuzzy rule induction and Rough Set approach is that, generally, Fuzzy set theory does not allow an information reduction process based on the relevance of particular subsets of attributes (reducts and core). Rough set approach has specific advantages also in comparison with standard statistical analysis. In fact the "*if . . . , then . . .*" decision rules of Rough Set approach are expressed in a natural and easily understandable language without any specific competence. Moreover, statistic analysis, generally, needs that the considered data must be representative and the object distributions in the decision classes must be well-balanced: very often a normal multivariate distribution of attribute values is required. The Rough set approach does not require any of these constraints; this is due to its specific characteristic which permits to assign to each decision rule the objects from which it was induced. Thus the user has all the elements to interpret the decision rules which constitute a full transparent representation of the analysed data. The transparency of the Rough Set approach is an important advantage also with respect to some other techniques of artificial intelligence as neural networks.

The concept of Rough Set theory is based on the assumption that with every object of the universe (U) there is associated a certain amount of information (data, knowledge), expressed by means of some attributes (Q) used for object description. More precisely, these information can be represented in a *data table* in which rows refer to distinct objects and columns refer to the considered attributes. Each cell of this table indicates, therefore, a description (quantitative or qualitative) of the object placed in that row by means of the attribute in the corresponding column. If in a data table the set of attributes (Q) is divided into *condition* attributes (set $C \neq 0$) and *decision* attributes (set $D \neq 0$), with $C \cup D = Q$, such table is called *decision table*. Since it illustrates the functional dependencies between condition and decision attributes, a decision table may also be seen as a set of *decision rules*. These are logical statements of the type "*if ..., then* ...", where the antecedent condition part (*if*) specifies the value(s) assumed by one or more condition attributes, and the consequence decision part (*then*) specifies the values assumed by the decision attribute(s). Objects having the same description are indiscernible (similar) with respect to the available information. The *indiscernibility relation* induces a partition of the universe into blocks of indiscernible objects (elementary sets) that can be used as "bricks" to build knowledge about a real or abstract world. Any subset X of a universe may be expressed in terms of these elementary sets either precisely (as a union of elementary sets) or approximately only. In the latter case, the subset X may be characterized by two ordinary sets, called *lower* and *upper approximations*. The lower approximation of X is composed of all the elementary sets completely included in X (whose elements x, therefore, certainly belong to X):

$$\underline{P}(X) = \{x \in U : I_P(x) \subseteq X\} \tag{1}$$

where I_P represents the indiscernibility relation on U with respect to a non-empty subset of attributes $P \subseteq Q$ and $I_P(x) = \{y \in U : yI_Px\}$ are the equivalence classes of $x \in U$. The upper approximation of X is composed of all the elementary sets which have a non-empty intersection with X (whose elements x, therefore, may belong to X):

$$\overline{P}(X) = \left\{x \in U : I_P(x) \bigcap X \neq \emptyset\right\} \tag{2}$$

The difference between the upper and lower approximations constitutes the boundary region of the Rough Set, whose elements cannot be characterized with certainty as belonging or not to X, using the available information. The information about objects from the boundary region is, therefore, inconsistent or ambiguous. For this reason, the number of objects from the boundary region may be used as a measure of vagueness of the information about X.

The definition of the approximations of a subset $X \subseteq U$ can be extended to a classification, i.e. a partition $Y = \{Y_1, \ldots, Y_n\}$ of U. The subsets Y_i, $i = 1, \ldots, n$, are disjunctive classes of Y. By P-lower (P-upper) approximation of Y we mean sets $\underline{P}(Y) = \{\underline{P}(Y_1), \ldots, \underline{P}(Y_n)\}$ and $\overline{P}Y = \left\{\overline{P}(Y_1), \ldots, \overline{P}(Y_n)\right\}$, respectively. Thus, the index:

$$\gamma_P(Y) = \frac{\sum_{i=1}^{n} |\underline{P}(Y_i)|}{|U|} \tag{3}$$

is called *quality of the approximation of classification Y* by set of attributes P, or in short, quality of classification. It expresses the ratio of all P-correctly classified objects to all objects in the universe.

Another important concept is that of "superfluous" attributes in a decision table. Superfluous attributes can be eliminated, in fact, without deteriorating the original classification. Let $P \subseteq Q$ and $p \in P$, the attribute p is *superfluous* in P if $I_P = I_{P-\{p\}}$; otherwise, p is *indispensable* in P. The set P is *independent* if all its attributes are indispensable. The subset $P^{'}$ of P is a *reduct* of P (denotation Red(P)) if $P^{'}$ is independent and $I_{P'} = I_P$. A reduct of P may also be defined with respect to an approximation of a partition Y of U. It is then called *Y-reduct* of P (denotation $Red_Y(P)$) and specifies a minimal subset $P^{'}$ of P which keeps the quality of classification unchanged, i.e. $\gamma_{P'(Y)} = \gamma_{P(Y)}$. In other words, the attributes that do not belong to *Y-reduct* of P are superfluous with respect to the classification Y of objects from U. The set containing all the indispensable attributes of P is known as the Y-*core*. Since the Y-core is the intersection of all the Y-reducts of P, it is included in every Y-reduct of P. It is the most important subset of attributes from P because none of its elements can be removed without deteriorating the quality of classification.

Finally the rough set approach leads to the induction of a set of decision rules representing the knowledge contained in the decision table. Each rule is supported by a certain number of objects from U. More precisely an object $x \in U$ supports a decision rule if its description matches both the condition and the decision part of the rule.

To select the most interesting rules the *relative support* and the *confidence level* for each rule are evaluated. The *relative support* is given by the ratio between the number of objects supporting the rule and the number of objects matching the decision part of the rule. The *confidence level* expresses the ratio between the number of objects supporting the rule and the number of all objects matching the condition part of the rule.

3. IMPLEMENTATION OF THE PROPOSED APPROACH

3.1 The study area

The Rough Set approach based on the *indiscernibility relation* was integrated and applied for discovering historical monthly operating rules of the main reservoir with irrigation purposes in Eastern Sicily (Table 1). The reservoir supplies about 20 000 ha of Catania Plain, mainly (90%) cultivated with citrus orchards. The distribution network is supplied by Simeto river; irrigation volumes are delivered at fixed intervals and applied by microirrigation methods. The precipitation in the irrigation district, gauged at 4 sites in the period 1921-1996 by the National Hydrographic Service, presents an average of 473 mm/year with a maximum of 863 mm (in 1969) and a minimum of 195 mm (1981). Stored volumes into the reservoir, evaluated by an hydrometer and the reservoir area-volume relationship, show a high interannual variation spanning between 97.0 10^6 m^3 in 1973 and 3.0 10^6 m^3 in 1990. Average annual evaporation losses from the reservoir amount to about 4.0 10^6 m^3.

The Catania Plain district experienced frequent shortages with the occurrence of 18 drought periods characterized by a mean duration of 1.53 years and a cumulated deficit of about 238 mm (Cancelliere and Rossi, 2003). The water volume released for irrigation presents a mean value of about 70.0 10^6 m^3, with a minimum of 2.5 10^6 m^3 in 1990, and appears strictly related to fluctuations of inflow and stored volume. Pluriannual regulation of the reservoir is not practiced, so that, for example, during the most severe drought (1988-1990), the annual release was only 4% of the average.

3.2 Methodology

The hydrological system-state variables provided by the reservoir balance applied to the 39 years from 1964 to 2002 were processed according to the following procedure.

Historical monthly release from the reservoir throughout the irrigation season was treated as the decision attribute. In reservoir operation problems the choice of condition attributes to explain the decision attribute is a crucial step. A good knowledge of the system to be described is essential so that a representative rule system may be obtained. The reservoir storage at the end of each of the first four months of the year and the release over the previous month were assumed as the attributes controlling the decision. As it is well known in semi-arid conditions the reservoir state is strictly related to winter inflows and, during the irrigation season (May to October), the downstream demands are large relative to the inflows. This causes the reservoir releases generally to depend almost exclusively on previous reservoir state. The *decision table*, showing the set of condition attributes (a_i) used to explain the decision attribute (d), is presented in Table 2.

In the case of decision attributes with continuous domain a preliminary discretization is required, in order to get a description of the phenomenon studied without noisy details. Thus, the decision attribute was discretized through a two-step procedure. In the tentative discretization, the minimum historical release in the month m of the irrigation season (r_m; with $r_m \neq 0$) and the maximum one (R_m) were determined; the number of release classes (n_m) was set to the integer number closest to

$$\frac{R_m - r_m}{r_m} \tag{4}$$

where r_m represents the lowest historical release (always equal to zero in the case-study).

Then empirical distributions of monthly release represented in Figure 1 were fitted with analytical distributions (normal for June, July and August, log-normal for May, September and October). An empirical distribution is influenced by outlying data (peaks of the distribution) while the analytical distribution permits a regularization of the data and allows to build, in the next step, decision classes with homogeneous data.

The lower and upper bounds of the i-th release class, respectively x_{i-1} and x_i, $\forall i = 1, ..., n_m$, are determined in such a way that all the classes have equal probability of occurrence (Clasadonte *et al.*, 2003) with respect to the analytical distribution $f_m(x)$ of historical monthly water release from the reservoir:

$$\int_{x_{i-1}}^{x_i} f_m(x)dx = \frac{1}{n_m} \tag{5}$$

where $x_0 = r_m$. This kind of discretization, with decision classes of unequal width, allows to build "robust" decision classes also with respect to the tails of the analytical distribution,

Table 1. Main characteristics of Pozzillo reservoir and irrigated area

Net Capacity ($10^6 m^3$)	Catchment area (km^2)	Annual streamflow* ($10^6 m^3$)			Annual release ($10^6 m^3$)			Irrigated area ($10^3 ha$)	Main crop	Irrigation season
		Min	Mean	Max	Min	Mean	Max			
140	577	3.3	120	295	2.5	68	120	20	citrus	May-October

*as evaluated for the hydrologic year

Table 2. Definition of decision and condition attributes used in the case study

Decision attribute	
d	Monthly released volume throughout the irrigation season
Condition attributes	
a_1	Stored volume at the end of January
a_2	" " " February
a_3	" " " March
a_4	" " " April
a_5	Released volume in the previous month

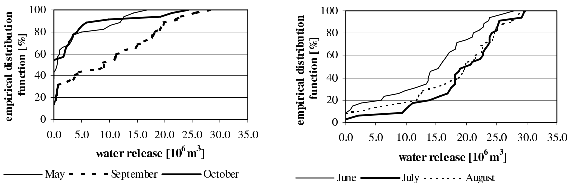

Fig. 1. Empirical distribution function of monthly water release at Pozzillo reservoir (1964 to 1988)

in which the rare events are grouped in decision classes of greater width. The results of release re-discretization are reported in Table 3.

Table 3. Discretization of decision attribute for Pozzillo reservoir

Month of the irrigation season	Water release range $[10^6\ m^3]$	Number of water release classes (n_m)	Width release classes $[10^6\ m^3]$	
			Tentative discr.	Re-discr.
May	$[0.0-17.5]$	7	2.5	$0.3-7.2$
June	$[0.0-30.0]$	4	7.5	$5.4-8.8$
July	$[0.0-30.0]$	3	10.0	$6.0-16.3$
August	$[0.0-40.0]$	4	10.0	$5.7-16.3$
September	$[0.0-30.0]$	6	5.0	$1.6-13.7$
October	$[0.0-25.0]$	7	3.5	$1.0-12.9$

The software *Rose* (Predki *et al.*, 1998; 1999) developed by IDSS (University of Poznan, Poland, 2000) was applied to the decision table in order to discretize condition attributes with continuous domains into the ones with discrete domains (Fayyad and Irani, 1992). Condition attributes were discretized in order to obtain very general rules instead of local rules that could be non-informative because too specific. More generally, within the Rough Set analysis, a good discretization permits to obtain quite significative results (reducts, core and quality of classification). The following *Shapley* index (Shapley, 1953) was used to evaluate, within the discovered set of reducts, the importance of a single condition attribute a_i ($\forall i = 1, \ldots, 5$) in terms of *quality of classification* (Greco *et al.*, 2001):

$$\Phi_S(a_i) = \sum_{K \subseteq P - \{a_i\}} \frac{(n - |K| - 1)!\,|K|!}{n!} \times \times [\gamma(K \cup \{a_i\}) - \gamma(K)] \quad (6)$$

where P is the set of condition attributes, K represents all the subsets obtained from set $P - \{a_i\}$, $|\cdot|$ denotes the cardinality of the subsets, n is the number of attributes belonging to P and γ is the *quality of classification*. The *Shapley* index can also be used to recognize the most significant combinations of condition attributes (Greco *et al.*, 2001). To determine the relevance of possible combinations of attributes the following generalized *Shapley* index (Grabisch, 1997) was herein applied to Rose outputs:

$$\Phi_S(A) = \sum_{K \subseteq P - A} \frac{(n - |K| - |A|)!\,|K|!}{(n - |A| + 1)!} \times \times \sum_{L \subseteq A} (-1)^{|A|-|L|} [\gamma(L \cup K)] \quad (7)$$

where A represents the combination sub-set of condition attributes, K the remaining combination subsets ($P - A$), L all possible subsets of attributes from A. Positive values of Φ_S indicate that the evaluated subset of condition attribute(s) is able to improve the *quality of classification* of the decision attribute, with respect to each condition attribute of the examined subset. By comparing the subsets of attributes, with the same cardinality, only the subsets with highest values of Φ_S (with $\Phi_S > 0$) were processed by *Rose* package and monthly operating rules discovered as logical statements in the form "*if* ..., *then* ...". The operating rules with the highest confidence level and relative support over the threshold of 75% and 25% respectively were selected using an easy to read spreadsheet. Generally, confidence level and relative support should be at least equal to the posed thresholds to assure the reliability of the discovered rough set criteria (Dimitras *et al.*, 1999; Clasadonte *et al.*, 2004).

4. RESULTS AND DISCUSSION

Rose application provided the minimal set of condition attributes (*reduct*) maintaining unchanged the *quality of classification* of equation 3 (Table 4). For all months only one reduct was determined representing also the core of the set of condition attributes. Stored volume at the end of April

(a_4) and release during the previous month (a_5) were recognized as belonging to all the discovered reducts derived from *Rose* application. This would mean that Pozzillo reservoir has been usually operated according to a short-term policy partially established at the beginning of the irrigation season.

Table 4. Outputs of Rose application to the decision table build for Pozzillo reservoir

Month of irrigation season	Quality of classification	Reduct a_1	a_2	a_3	a_4	a_5
May	1.0	X	X	X	X	
June	1.0	X		X	X	X
July	1.0	X	X		X	X
August	1.0		X	X	X	X
September	1.0	X	X	X	X	X
October	1.0	X	X		X	X

Condition attributes, as recognized by applying the *Shapley index* of equation 6 and 7, are shown in Table 5.

Table 5. Condition attributes screen out by the Shapley index

Month of irrigation season	Quality of classific.	Shapley Index	Cond. attributes a_1	a_2	a_3	a_4	a_5
May	0.09	0.09	X				
	0.54	0.46	X		X		
	0.66	0.06	X		X	X	
June	0.26	0.26	X		X		
	0.71	0.20	X		X		X
	1.00	0.06	X		X	X	X
July	0.17	0.17					X
	0.63	0.46	X				X
August	0.06	0.06			X		
	0.31	0.26			X		X
	0.86	0.20		X	X		X
September	0.09	0.09	X				
	0.14	0.06	X				X
	0.29	0.12	X			X	X
	0.74	0.09	X	X		X	X
October	0.03	0.03	X				
	0.71	0.69	X				X
	0.86	0.06	X	X			X

The most significant operating rules were thus individuated as representative of the historical management of Pozzillo reservoir (see Table 6).

The discovered rules can be explained using an easy logical form; for example, in Table 6 the 3^{rd} rule for June can be read as: *if* stored volume in January is in the range $[60.7 - 132] \times 10^6\ m^3$, and the stored volume in March is in the range $[68.7 - 99.5] \times 10^6\ m^3$, *then* release in June is in the range $(14.3 - 19.7] \times 10^6\ m^3$. This rule covers 33% of the objects belonging to the explained decision class with a confidence level of 100% (more precisely, this rule explains the releases in the month of June in the years 1970, 1997 and 1998).

The analysis of the discovered operating rules highlights a releases strategy generally based on a two-stage framework. First, the decision maker examines for later use the state of the reservoir (stored volumes) in January and/or February, taking available information on inflow changes into account. Second, the decision maker, according to the first phase of the decision process, refines the operating rules set according to water availability at the end of March and/or April, and/or at the month before that of release. Furthermore, volumes are released using a typical Standard Operating Policy (SOP), providing release volumes which increase with water availability in the reservoir without any hedging. In particular, by using a SOP procedure, reservoirs are depleted to meet downstream demands without taking into account the probability of future shortage periods occurrence (Yeh, 1985).

To generalize, the discovery of operating rules was also tried working on a larger set of condition attributes (Table 7), including inflows and stored volumes within the hydrological year (November to October). The use of inflow data could be however limited by the availability of runoff data or the pretreatment effort (rainfall-runoff transformation).

By analysing the outputs of this trial (on the anlarged set of condition attributes), it can be argued that:

- Rose package implementation individuated several reducts in the enlarged decision table for all months of the irrigation season; the intersection between the discovered reducts (core) is an empty set;
- the combination of condition attributes, according to the Shapley index, and the decision rules discovered confirm the results previously (Table 6); the only new pertains to the three condition attributes combination (stored volume at the end of January, inflow of March and released volume in the previous month) induced for October that does not allow to explain the high level of release (explained in the last rule of Table 6).

5. CONCLUSIONS

The proposed integrated Rough Set approach allowed to exploit the reservoir hydrological and operational information in order to work out historical release operating rules. The implemented approach:

- supplies useful elements of knowledge about reservoir operating rules such as relevance of attributes, information about their interaction (from *quality of classification*), minimal subsets of attributes (*reducts*) conveying the relevant knowledge contained in the operat-

Table 6. Operating rules for water release from Pozzillo reservoir as discovered by the integrated Rough Set approach

Month	Condition attributes ($10^6 m^3$) Stored volume Jan (a_1)	Feb (a_2)	Mar (a_3)	Apr (a_4)	Release in the previous month (a_5)	Min\Max width of release class ($10^6 m^3$)	Support (%)	Confidence level (%)
May	$[13-22]$		$[2.9-65.1]$			$[0-0.3]$	27	100
Jun	$[0.9-22]$		$[2.9-68.3]$	$[3.7-48.5]$	$[0-0.6]$	$[0-8.8]$	55	100
	$[0.9-22]$		$[2.9-68.3]$	$[49.4-132.2]$	$[0-0.6]$	$(8.8-14.3]$	28	100
	$[60.7-132]$		$[68.7-99.5]$			$(14.3-19.7]$	33	100
	$[60.7-132]$		$[99.6-130]$		$[0.7-16.8]$	$(19.7-30]$	40	100
Jul					$[14-16.9]$	$(22.3-30]$	40	100
Aug			$[2.9-36.1]$		$[0-5.8]$	$[0-12.2]$	50	100
		$[60.3-133]$	$[39.6-99.6]$		$[18.1-27.8]$	$(23.7-40]$	40	100
Sep	$[0.9-60.7]$	$[2.9-35.2]$		$[3.7-74.3]$	$[0-11.9]$	$[0-1.6]$	45	100
	$[0.9-60.7]$	$[37.2-133]$		$[74.5-132]$	$[24.3-30.1]$	$(6.5-12]$	50	100
Oct	$[2.6-42.6]$				$[0-11.5]$	$[0-1.9]$	76	100
	$[84.3-132]$	$[122.4-133]$			$[19.8-28.4]$	$(12.1-25]$	67	100

Table 7. Definition of decision and condition attributes used in the Pozzillo reservoir case study

Decision attribute	
d	Monthly released volume throughout the irrigation season
Condition attributes	
$c_1 \div c_{11}$	Stored volume at the end of the months November to September
$c_{12} \div c_{22}$	Inflow of the months November to Sept.
c_{23}	Released volume in the previous month

ing rules, set of the non-reducible attributes (*core*);

- expresses the operating rules in the natural and understandable form *if ..., then ...*;
- involves low cognitive efforts for the user (also in the case of large decision tables): more precisely, the user must provide only the decision attribute discretization. The Rose package allows to perform all calculations in real-time so that few hours at most are enough to process an established database;
- operates on original data without require statistical operators such as average and standard deviation;
- involves elementary concepts and mathematical tools, without recourse to any analytical structures.

Further research would tend to develop and refine the integrated approach to improve the exploitation of operation and hydrological information on the reservoir for defining its operations, by introducing:

- *deficit irrigation* criteria: to evaluate any acceptable reduction in water supply for irrigation needs, during water shortage periods, taking into account crop yield response;
- forecast criteria: to assess the effectiveness of the proposed approach to recognize decision criteria by considering the uncertainty on inflow data.

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