ISSN 1996-3343

Asian Journal of Applied Sciences

http://knowledgiascientific.com

Knowledgia SCIENTIFIC
A Place to Publish Outstanding Research

Asian Journal of Applied Sciences 4 (5): 493-513, 2011
ISSN 1996-3343 / DOI: 10.3923/ajaps.2011.493.513

Optimal Reservoir Operation for Irrigation of Multiple Crops using Fuzzy Logic

M. Hosseinpourtehrani and B. Ghahraman
Department of Water, Faculty of Agriculture, Ferdowsi University of Mashhad, Mashhad, Iran

Corresponding Author: M. Hosseinpourtehrani, Department of Water, Faculty of Agriculture, Ferdowsi University of Mashhad, Mashhad, Iran Tel: +9821-33342534 Fax: +9821-33352072

ABSTRACT
In this study, a Fuzzy based model using a non-linear programming to obtain optimal reservoir operation for irrigation of multiple crops is proposed. The reservoir level Fuzzy logic model can extract important features of the system from the input-output data set by non-linear programming and represents features as general operating rules. The developed model can serve not only as efficient decision making tool in easy and understandable Fuzzy inference systems but also can provide operators with a limited number of the most meaningful operating rules using clustering-based approach. The model is set properly in a yearly base and monthly steps. Results show that the changing trend of water releases in both models is the same with $R^2 = 0.97$. Over the 12 months period, both trends had risen from October to May but since then they had fallen gradually. In general the amount of annual released water in Fuzzy model is almost less than NLP, especially in competitive months, May and June. The percentage of water deficit to the percentage of annual mean water deficit was respectively 0.57 and 0.81 in training and 0.93 and 1.145 in the test stage. In addition, the water deficit compared with the amount of cultivated crops acreage has more impact on Net Benefit. Also, allocating less water to wheat compared with barley and sorghum had significant effect on the yield production. The findings suggest that in the year with water deficit the amount of water release in competitive months to increase the Net Benefit should be more considered.

Key words: Reservoir operation, non-linear programming, fuzzy model, clustering, yield production

INTRODUCTION
Water shortage and growing water demand, particularly in arid and semi-arid areas, is a worldwide issue. So considering efficient management of limited water resources in irrigation reservoir operation policy is necessary to increase crop productivity. Also, an irrigation reservoir operation policy should reflect the economic value of stored versus released water. So in making decision for reservoir operation both reservoir level and farm level should be considered (Reddy and Kumar, 2007).

For optimal allocation of irrigation water, different models were developed based on the basic classification of optimization techniques consists of Linear Programming (LP), Dynamic Programming (DP) and Non-Linear Programming (NLP). Each of these techniques has been applied in a deterministic and stochastic environment for planning purposes as well as real-time operation. So each method has a certain distinguishing feature that separates it from the others. An excellent review of the topic is given by Labadie (2004). A comparative study on the applicability and computational difficulties of these models is presented by Mujumdar and Narulkar (1992) and Azamathulla *et al.* (2008).

Borhani and Eftekhar (2005) presented and compared various types of stochastic dynamic programming models and also deterministic dynamic programming for multipurpose dez reservoir dam located in southwest of Iran.

Vedula and Mujumdar (1992) used a two-stage Dynamic Programming (DP)-SDP to obtain a steady state optimal reservoir operating policy for irrigation of multiple crops. Vedula and Kumar (1996) developed an improved model using a two-stage Linear Programming (LP)-SDP approach considering the soil moisture balance independently for each crop and actual evapotranspiration in order to obtain crop-water allocation and the steady-state optimal operating policy (Reddy and Kumar, 2007).

A significant contribution to the real-time reservoir approach was presented by Mujumdar and Ramesh (1997) who addressed the issue of short term real-time reservoir operation by forecasting the inflow for the current period, a crop production state variable and a soil moisture state variable. Their work was based on SDP but had all the limitations of SDP regarding the curse of dimensionality (Azamathulla *et al.*, 2008).

It is also noted that in a short-term yearly reservoir operation model SDP-based steady state are not used as they are useful for maximizing the long-term benefits from an irrigation system. LP models have also limitation since various functional relationships are assumed to be linear whereas this will not reflect the actual situation in the field (Reddy and Kumar, 2007).

Among optimization methods stated above Non-Linear Programming (NLP) has been treated extensively in the literature of operation research that offers a more general mathematical formulation of the reservoir problem (Simonovic, 1992). In this way, Ghahraman and Sepaskhah (2002) developed a model using a two-stage (NLP)-SDP. In the first step they maximized the total farm income in a season. In the second step for the convergent operating policy over seasons for optimal expected farm income over a year.

Reddy and Kumar (2008) also proposed Multi-Objective Differential Evolution (MODE) approach for a multi-crop irrigation reservoir system. A nonlinear multi-objective optimization model to maximize total net benefits by irrigating high economic value crops includes water-intensive crops and a longer duration crop is formulated. They concluded that because of considerable impact of the hydrologic conditions on net benefits and cropping pattern using this model can be helpful for irrigation planning and reservoir policies to select the best possible solution.

Kangrang and Compliew (2010) used an allocation LP model to find an optimal crop pattern. They take into account heterogenetity of water demand and yield of irrigation area for crop in their aim. They also used a sensitivity analysis of irrigation efficiency in modified LP model. Results showed that LP model is feasible for finding the optimal crop pattern.

A simulation model is usually characterized as a representation of a physical system used to predict the response of the system under a given set of conditions. The simulation model is not able to generate an optimal solution to a reservoir problem directly. However, when making numerous runs of a model with alternative decision policies it can detect an optimal or near-optimal solution (Simonovic, 1992).

Simulation models as a prominent tool for reservoir systems planning and management studies are more practible compared with optimization techniques. Simulation models associated with reservoir operation are usually based on mass balance equation and represent the hydrological behavior of reservoir systems using inflows and other operating conditions. Some models however, represent economic performance of the reservoir system. Simulation could be the starting point in the planning of large scale systems but in view of the very large number of options of configuration, capacity and operating policy, simulation without preliminary screening through optimization would be very time consuming (Rani and Moreira, 2010).

In the recent past, the Fuzzy logic techniques as a kind of simulation model in the form of if-then rules (i.e., human like reasoning in linguistic terms) play a deserving role to simplify complicated non-linear functions models with simpler ones (Russel and Campbell, 1996; Shrestha *et al.*, 1996; Hasebe and Nagayama, 2002; Panigrahi and Mujumdar, 2000; Dubovin *et al.*, 2002). Fuzzy logic are also suitable in models with multi- input and single output control variables which have been used jointly with stochastic modeling (Mousavi *et al.*, 2007). Methods for deriving a rule base from observations in reservoir operation are presented by Tilmant *et al.* (2002), Teegavarapu and Simonovic (1999) and Dubovin *et al.* (2002), with the difference that the expert knowledge for making Fuzzy Rule based (FR) are either derived from implicit stochastic models or explicit ones (Mousavi *et al.*, 2005).

Comparison between Fuzzy inference System and other Artificial Intelligence Models such as ANN and ANFIS in Water Resources Management are also studied by Mpallas *et al.* (2011), Dastorani *et al.* (2010) and Tareghian and Kashefipour (2007).

Due to complexity of optimization models and deviation of the their results from the reality these models are used along with simulation models to permit very detailed representation of complex physical, economic and social characteristics of a reservoir system. The concepts inherent in the simulation approach are easier to understand and make flexible operational rules in reservoir operations (Depic and Simonovic, 2000). Moreover, the optimal releases obtained by optimization models are not useful much in that form for operators in the future well. Therefore, to solve this problem optimal time series, derived by an optimization model in the first step, are reformed as some general operational rules in the second step, which are easier to use for operations in the future (Ponnambalam *et al.*, 2001). Mousavi *et al.* (2007) examined Fuzzy rule base in deriving operating rules for reservoir operations optimization problem. The model was an implicit stochastic optimization model for synthetically generated inflow scenarios having one year of horizon each. This model used to decide how much release should be made from the reservoir in each time period of a representative planning horizon minimizing the sum of total deviations of releases from target releases. The optimal sets obtained from the above model are then used in inferring operating rules using Fuzzy Rule based (FR). Based on the results derived by Mousavi *et al.* (2007), making decision for general operational rules at reservoir level is possible, however, the point is the objective function of Mousavi *et al.* (2007) cannot satisfy the decisions at the field level.

Rani and Moreira (2010) presented a review on different approaches of simulation and optimization modeling in operating reservoir systems. They studied different articles about application of simulation models such as evolutionary computations, Fuzzy set theory and artificial neural networks, classical optimization techniques and combined simulation-optimization modeling. The outline of this survey can be helpful for future research to decide appropriate methodology for application to their system.

Extensions of NLP to stochastic cases are rare due to intense computational requirements and few applications are reported in literature. Also, it can be noticed that in recent years interest has grown in using heuristic approaches as an alternative to NLP, as they can easily handle both nonlinearity and uncertainty (Rani and Moreira, 2010). However, none of the above-mentioned studies used NLP as optimization methods to derive the Fuzzy rules for optimal operation of reservoir systems. Moreover, in spite of gaining popularity of Fuzzy logic techniques, Fuzzy inference system also suffers from the problem of a large number of rules. The concept of clustering to reduce Fuzzy rules is extended in some studies. According to the study of Sivapragasam *et al.* (2007), one effective way to reduce the rules is to use fewer numbers of Fuzzy sets by dividing the training data into a number of clusters. It is easy to represent the inputs by fewer Fuzzy sets by classifying the similar inputs into a given class. By classifying the similar inputs into a given class, it is easy to represent the inputs by fewer Fuzzy sets. Based on above-mentioned study to reduce the Fuzzy rules in highly condensed and meaningful rules we consider single triangular membership function together with the clustering methods with the difference that the structure of clustering in this study is based on main cluster and subclusters by K-mean clustering algorithm.

The purpose of this study is to establish a synthesized model relied on objective function by Ghahraman and Sepaskhah (2004) at the field level and the Fuzzy model by Mousavi *et al.* (2007) at the reservoir level. A Fuzzy model base reservoir operation model using a non-linear programming to obtain optimal sets to it is run for multiple crops. The model has two steps. At the reservoir level the amount of water available according to the objective function. At the field level, the model considers monthly competition for water among multiple crops in each cropped area and crop response to the water obtained by Fuzzy model. What is more, in each year input data including monthly generated inflow series, water demand and storage volume used in non-linear programming. Monthly released volume as output data are extracted from non-linear programming. Then, the optimal values obtained from a Non-Linear Programming (NLP) model with input values are used in a Fuzzy Rule-Based (FRB) model to derive the operating policies (NLPFBR). Filling the gap by comparing policies derived from the NLPFBR model and its equivalent classical (crisp) NLP formulation has been considered in this study. To expand the Fuzzy model, the description of clustering model is presented.

MATERIALS AND METHODS

Case study: Ilanjogh, a single purpose reservoir in the north of Khorasan province is chosen as a case study in 2007. This reservoir is supplied from Zangelanloo river.

Daregaz basin with 3129 km^2 is located in the north of the Allahoakbar mountain. Zangelanloo river originated from the southeast Daregaz mountain is extended to Turkmenistan in the east of Daregaz. It is supposed that Ilanjogh dam will provide agricultural water needs of this region. water resources system plan is shown in Fig. 1.

Implementation of Non-Linear Programming as an optimization tool: Objective function is set to maximize the Net Benefit of cultivation as follows:

$$\text{MAX}: \sum_{k=1}^{f} \sum\nolimits_c A_c \left[B_c \left(Y_a / Y_p \right) - C_c \right] \tag{1}$$

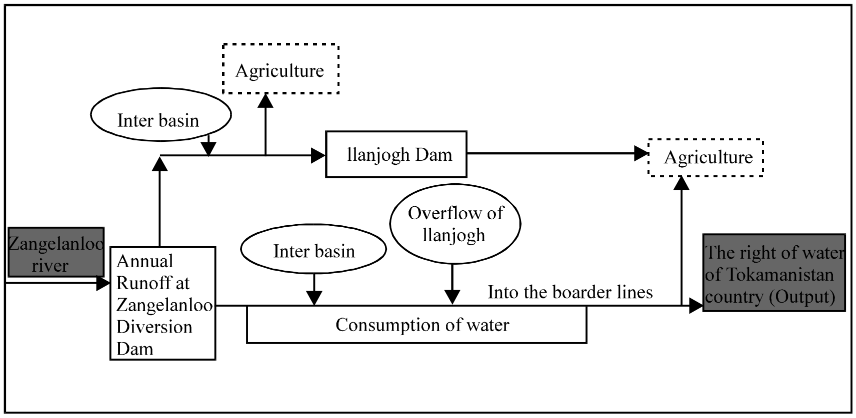

Fig. 1: Scheme of the water resources system of llanjogh dam

where, A_c is the cultivated area of different crops including wheat, barley and sorghum, f is the number of fields, B_c is the benefit (price ha^{-1}) and C_c is the cost (price ha^{-1}) for each crop, Y_a/Y_p is relative yield. In this formula the only unknown variable is Y_a while the other variables are either measured (e.g., A_c, B_c, C_c) or accounted for (e.g., Y_a).

The water product function is:

$$\frac{Y_a}{Y_p}=\prod_{i=1}^{N}\left[1-K_{yi}\left(1-\frac{ET_a}{ET_p}\right)\right] \tag{2}$$

where, Y_a is the actual yield, Y_m is the maximum yield, i is a generic growth stage, N is the number of growth stages considered, K is the yield response factor at growth stages i and ET_a and ET_m are the actual and maximum evapotranspiration, respectively. Water which can be allocated as ET_a can be available from the reservoir, on which the following constraint is governed:

$$V_{t+1} = V_t + Q_t + REL_t - EVP_t - OVF_t + RAIN_t \tag{3}$$

where, V_t and V_{t+1} are the state of storage volume of reservoir at the beginning and the end of month t, respectively, Q_t and $RAIN_t$ are inflow to the reservoir and direct rainfall over the reservoir area during month t, respectively, REL_t and OVF_t are release and overflow volume from the reservoir and EVP_t is the evaporation lost from the reservoir during month t. The amount of water available during the month t (i.e., V_t) is logically bounded by dead storage (Vdead) and maximum capacity of the reservoir (V_{max}):

$$V_{dead} \le V_t \le V_{max} \tag{4}$$

The conveyance efficiency (assumed 0.9) is used to convert the released water from the reservoir to the amount of water paid for crop irrigation:

$$IR_t = E_c.REL_t \tag{5}$$

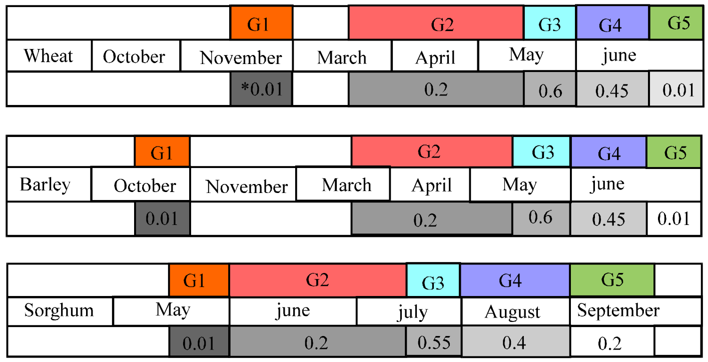

Fig. 2: Crop calendar used for command area of ilanjogh reservoir system. G1 to G2 are the establishment, vegetative, flowering, yield formation and ripening stage, respectively

the following term should be considered for different crops:

$$\sum_{c} IR_{c,t}.AREA_{c} = IR_{t} \tag{6}$$

The objective function coupled with the relevant constraints was managed through a non-linear optimization procedure from a single purpose reservoir operation (Doorenbos *et al.*, 1979; Ghahraman and Sepaskhah, 1999). Here we did not consider the water balance in soil and just approximated the ET_a/ET_p by the ratio of applied water to its optimum amount. To manage the relative yield, Y_a/Y_p, we adopted the sensitivity of crops to water from literature (Ghahraman and Sepaskhah, 2004) and changed them to the monthly scale. Figure 2 shows the 5 growth stages including establishment, vegetative, flowering, yield formation and ripening considered in this study. The year is divided into 2 unequal seasons of dormant and active seasons. In dormant season there is no summer crop in the field and all winter crops are dormant, yet all crops may be active in the other season. The dormant season in the region begins around the 22nd of November up to the 20th of February, so there is no release from the reservoir in this period. Considering that Wheat and Barley are winter crops and Sorghum is a summer crop, there is a competition between all 3 crops for water, especially in the middle and late of spring, when wheat and barley are going to be harvested and sorghum is in establishment phase. In this period of time there is a precise irrigation planning demand. Competing between 2 winter crops (wheat and barley) and summer crop (sorghum) in the time of wheat and barley cultivation and harvesting the sorghum, is very critical for irrigation management.

Compiling NLP by considering various cultivation areas and initial reservoir storage volume: Different scenarios are adopted to compile NLP because there is different volume of water in reservoir storage at the beginning of the year and also different combinations of Wheat-Barley-Sorghum cultivation area. Five cases are considered for active reservoir storage: empty (dead storage), full and 0.25-, 0.5- and 0.75-full storage. At present time, acreage of wheat, barley and sorghum are 478, 530 and 761 hectares, respectively.

To be more comprehensive, we defined two bands for wheat and barley acreages, respectively i.e., A and B. Another band is also defined for sum of acreages of wheat and barley (Table 1). Based on Table 1, different scenarios for crop acreages are considered that are presented in

Table 1: The constraints of barley and wheat acreage

Choice	Crop	Area
A	Wheat (WH)	$478\times1.1<{}^{a}A_{WH}<478\times0.9$
B	Barley (BAR)	$531\times1.1<{}^{b}A_{BAR}<531\times0.9$
C	(WH+BAR)	$A_T\times0.5\times1.1<A_{WH}+A_{BAR}<0.5\times0.9\times{}^{c}A_T$

[a]The area of wheat, [b] The area of barely, [c] Total area

Table 2: Different area states suggested for selected crops. A, B and C are defined in Table 1

Different area states	Choice 1	Choice 2	Choice 3	Choice 4
A_T	$1.1\times1770<0.9\times1770<A_T$			[a]1770
$A_{WH}+A_{BAR}$	C	C	No bound	No bound
A_{WH}	No bound	A	A	478
A_{BAR}	B	No bound	B	531

[a]Total acreage at present time (ha)

Table 2. Each acreage scenario in combination with each 5 classes of reservoir volumes is managed through maximization of objective function (Eq. 1) via NLP.

Decision variables effects on objective function: It is obvious that objective function includes two decision variables which have direct effect on the net benefit: water yield production and cultivated areas. To justify the same trend of decision variable and objective function, the water Yield productions in different stages of growth and areas as direct factor in the amount of benefit is investigated. The released water should be taken precisely into account because it is a variable in the Yield production and affect indirectly on the net benefit.

In addition, more area has more benefit, so we want to get the point to reduce the effect of area. In order to know which crop and area has the most effect on the economic objective function; precise study in each crop in different stages of the growth is inevitable. Moreover, we want to get reasonable results based on yield response factors and the amount of sensitivity for each crop particularly in more competitive months in the year with more deficiency.

Short-term data for training and testing: Three hundred samples of monthly inflow series which are synthetically generated by fragment methods, are considered as inputs in non-linear programming (Hosseinpourtehrani *et al*., 2009). At first monthly and annual stochastic rainfall sequences simulation are considered to generate data with long-term dependence or preserve historical records distribution function. Annual and monthly rainfalls for Dargaz station with 15 years records are satisfactory simulated by stochastic models. A first-order Markov process is used for annual data and the fragment method for monthly data. Then, 5 different initial storage volumes (empty, full and 0.25-, 0.5- and 0.75-full reservoir volume) and 4 different area states were set corresponding to the beginning of the cropping season, October month.

To evaluate the amount of water, which should be released from the dam reservoir in monthly steps to supply agricultural water, the monthly releases of non-linear programming are extracted as output. Thus, monthly inflows, demands and also initial storage volume to reservoir are considered as independent variables and monthly releases from reservoir extracted from NLP model are set as dependent output variables. The optimal sets obtained from the non-linear methods, are used in inferring general operating rules using Fuzzy logic each with one year of planning horizon for 300 years. Among 1500 years of monthly input-output data taken by NLP model half of them are used for training while the second half are used for testing and comparing the economic performance of Fuzzy model versus NLP one.

Implementation of Fuzzy logic in optimal reservoir operation: FIS parameters are determined from the data obtained by NLP. FIS models are used to infer the relation between premise part (independent variables; storage and inflow) and the consequent part (dependent variable; release from the reservoir), by representing them as Fuzzy IF-THEN rules.

Implementation of clustering method to expand the Fuzzy model: For each input-output pair, one single rule is used in optimal Fuzzy systems. By increasing the input-output data, the number of Fuzzy rules increases as well which causes two problems; building Fuzzy rules is time-consuming and systematical errors are likely to increase. Thus, clustering technique, which classifies the input-output data into identical clusters, may be an effective way to reduce the rules in Fuzzy inference system. Similar inputs are put into the same clusters. Therefore, each cluster is known as a representative of a specific rule and consequently the number of rules reduces to the number of clusters.

In this study, the training data are divided into different clusters by K-means-based clustering technique and each cluster is characterized by a single rule. K-means treats each observation of data as an object having a location in space. K-means clustering can best be described as a partitioning method. That is, the function K-means partitions the observations into K mutually exclusive clusters and returns a vector of indices indicating to which of the K clusters it has assigned each observation. This technique finds a partition in which objects within each cluster are as close to each other as possible and as far from objects in other clusters as possible (Shamkoueyan *et al*., 2009). Each Fuzzy set in each cluster has a single membership function for given variables. As stated before, the present study is based on short-term period in which each scenario includes one year. Consequently, 300 synthetically generated samples of inflow time series corresponding to 5 different initial reservoir storage volumes, leads to generation of 1500 input-output data in which 750 samples are used for training clustering and building Fuzzy rules and the rest are used in simulation for testing. All input variables in each cluster, i.e., river inflow, reservoir storage, irrigation demand and reservoir release volumes, are fuzzified with a single triangular membership function. Each membership function parameterized by its vertices (l, left vertex; c, centre and r, right vertex of the membership function) (Sivapragasam *et al*., 2007), as shown in Fig. 3. Clustering is used separately for each month of years. The K-mean clustering method is done in two steps: in the first step, according to the initial storage volume at the beginning of the growing season the storage volume in each month classified into 5 main different clusters with specific volume of inflow, demand and release. In the second step in every main cluster each variable (inflow, demand and release) falls into three sub clusters in accordance with silhouette width criteria. As a result, in each month there are 15 Fuzzy rules for making decision about the amount of released water from reservoir. The clustering is schematically shown in Fig. 4.

Assessment of the Fuzzy logic model: A part of NLP model data is used as historical data in Fuzzy model to make the Fuzzy rules. To assess the Fuzzy model, the trend of Fuzzy model output in testing phase should be similar to the historical data of NLP. Moreover, three performance

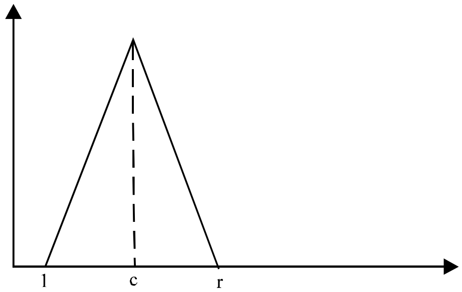

Fig. 3: Single trianglular membership function. 1, c and r representing left, center and right vertex of membership function, respectively

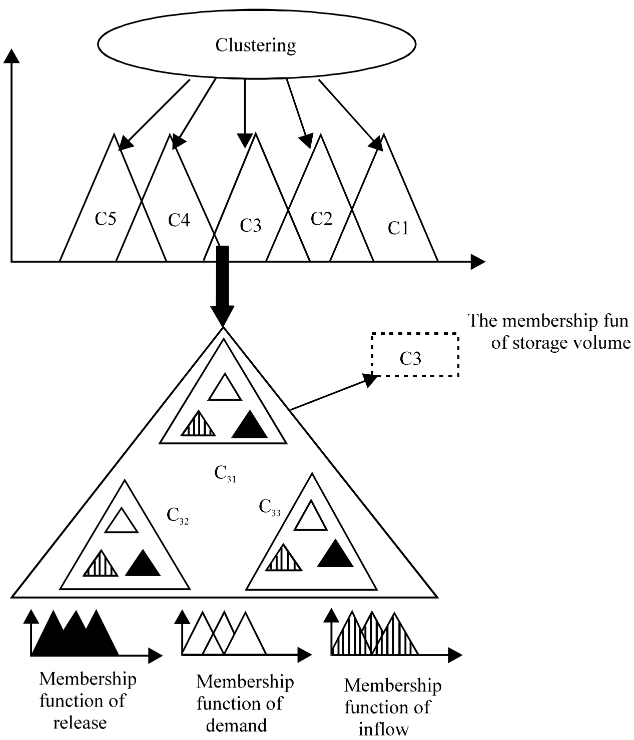

Fig. 4: The schematic example of clustering used in this study. C_1 to C_5 are the main clusters according to the initial storage volumes from dead to maximum one, respectively

measurements, i.e., R^2 (determination coefficient), MAE (Mean Absolute Error) and RMSE (Root Mean Square error) are introduced in the following equations to assess the performance of Fuzzy model:

$$R^2 = \frac{\left[\sum\left(r_0 - \bar{r}_0\right)\left(r_1 - \bar{r}_1\right)\right]^2}{\sum\left(r_0 - \bar{r}_0\right)^2 \sum\left(r_1 - \bar{r}_1\right)^2} \tag{7}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|r_0 - r_1\right| \tag{8}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(r_0 - r_1\right)^2} \tag{9}$$

where, r_0 and $\overline{r_0}$ are the value and mean value of the released water volume, respectively, extracted from NLP as observation data series (historical data) and r_1 and $\overline{r_0}$ are as same as the previous parameters but taken from Fuzzy model.

RESULTS

Non linear programming: For inferring operating rules in which the maximization of Net Benefit cultivated by crops in a yearly base is the objective function monthly storage, release and demand volume series were extracted from optimization model. Considering 5 different amount of it did the effect of initial reservoir storage at the beginning of water year by considering 5 different amount of it. In addition, the effect of 4 different cultivation area scenarios (Table 2) on monthly water release and demand was considered in the following.

Different initial storage volume: We adopted 4 different cultivation area scenarios (Table 2) and 5 different Initial Reservoir Storage Volume (IRSV) at the beginning of agricultural year (23 th October). For each case the NLP yielded the optimum reservoir release to reach the highest amount of Net Benefit. For each case of IRSV, we averaged the reservoir volumes for all cultivation area scenarios (Fig. 5). The results showed that for a specific condition for initial reservoir storage, the storage volume changed at different months (from October to September). This change would

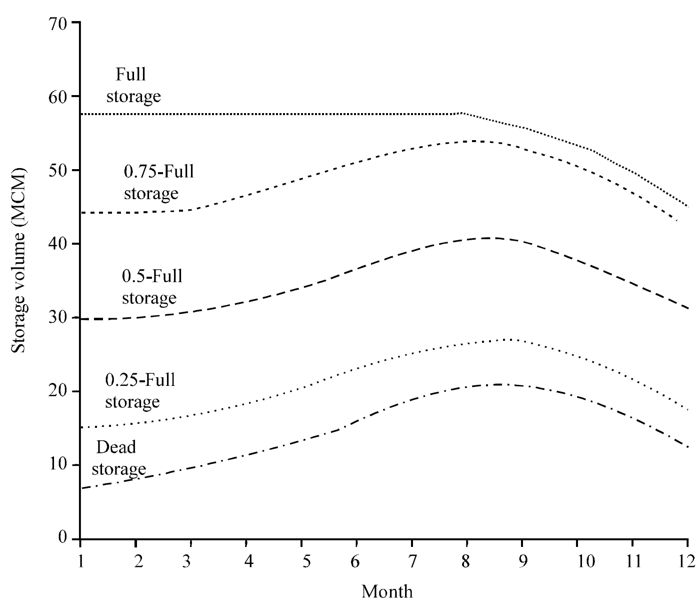

Fig. 5: Illustration of different optimal storage (MCM) paths. 1 is the beginning of the season growth (October)

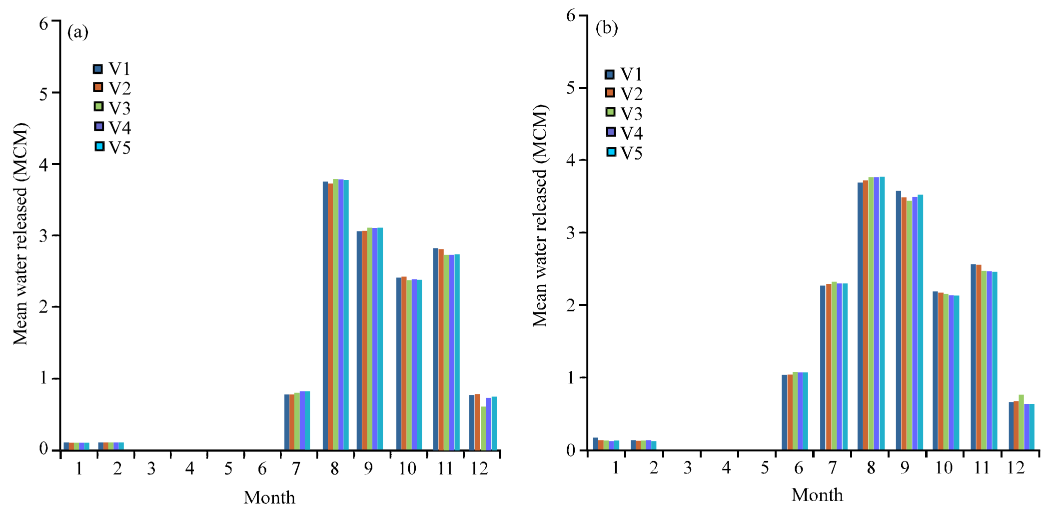

Fig. 6: Illustration of different optimal mean (a): Water released (CMC), (b): Water requirement (MCM): in order of increasing V1 to V5 is dead, 0.25-, 0.5-, 0.75- full storage and full

be in accordance with the amount of water needs. Figure 5 supports that the trends of these variations are independent of initial reservoir storage volume; meanwhile the trends are approximately parallel. Adopting a higher value for the initial reservoir storage also yields in higher reservoir storages at all months of the year. As shown in Fig. 5, reservoir storage increased up to months 7 and 8 (May and June) when there is a maximum competition between three crops for water demand. Two reasons can explain this trend: First of all the higher river inflow and secondly low water requirement. The stored water should be allocated afterwards to satisfy the irrigation requirements. Reservoir storage, then, decreases up to the end of the year, due to higher water requirement and also due to low river flow.

Monthly water release from the reservoir corresponding to different initial reservoir storages is shown in Fig. 6a. According to Fig. 6a, the average maximum release of irrigation with 5 different initial storage volumes occurs in May when all crops need water. Thus, it is logical to save much water in reservoir at preceding months when they need less water to release. It can be inferred from Fig. 6a that the amount of water released in a special month is nearly independent of initial storage volume such that it has almost identical results in different initial storage volumes. The result repeated in Fig. 6b showed that the amount of water requirement is independent of initial storage volume.

Different cultivation area scenarios: In a suitable irrigation reservoir operation, the optimum cultivated area and multiple cropping patterns are the most important factors for increasing the yield production and net benefit. Thus it is necessary to be sure about the efficiency of the model sensitivity analysis in different states of area with multiple cropping patterns.

In addition, the amounts of required and released water depend on the cultivation area. In fact, released water affects directly to the yield production, which has a crucial role in the amount of the net benefit. Figure 7 showed that the changing trend of released and required water in the downstream was almost the same over a year. Besides, the most deficits in different states of area occur in March and April when wheat and barley were in the second and third stages of the

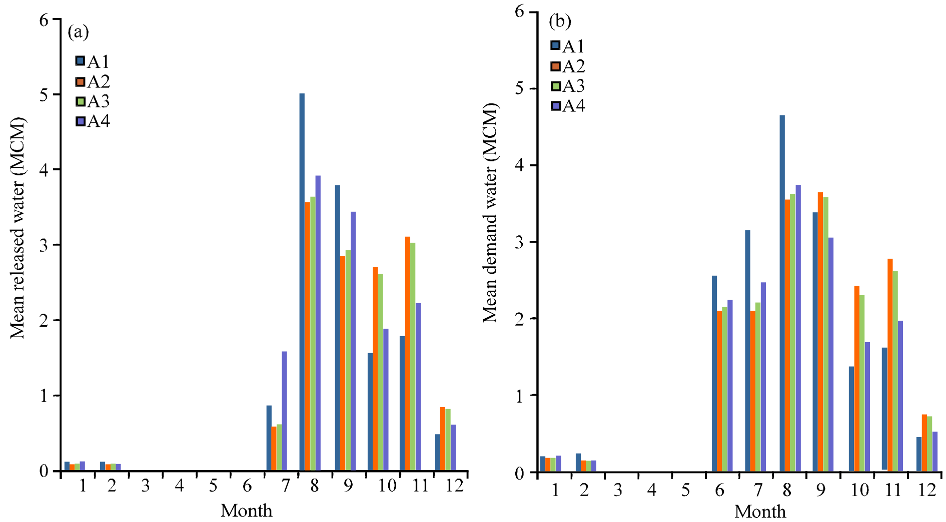

Fig. 7: Illustration of different optimal mean (a) released water, (b) required water (MCM) path. A_1 to A_4 are 4 different states area accordance with Table 2

growth. This trend was repeated in June when sorghum was in the second stage of the growth and Wheat and Barley were respectively in the fourth and fifth stages of the growth.

Fuzzy logic based model: As stated before, the results of NLP indicated that specific initial reservoir storage at the beginning of cropping season plays an effective role on the reservoir storage in other months and they were positively related to each other. Moreover, the clustering was more pronounced by this variable, as was compared with the other variables of reservoir release and agricultural demand. Using either of these last two variables, did not lead to a good fuzzification in each month. So we considered the membership function of reservoir storage volume in each month as main cluster, where each cluster had three sub-clusters including specified river inflow, demand and release. In this study, because storage volume in each month with specified initial storage volume at the beginning of the cropping season completely differed from the same month with other initial storage volume at the beginning of cropping season, we made the clustering based on reservoir storage as the best choice for classification. The Silhouette width criteria which tested the similarity of any member to the appropriate clusters, confirmed the results.

Membership functions for clusters: We used triangular membership functions in this study (Fig. 8, 9). μ was the degree of membership function and C represented the cluster, such that in C_i, j, i was the number of the main cluster and j was the number of sub-cluster corresponding to its main cluster. For instance, C_{12} showed the second sub-cluster corresponding to the first main cluster. The proximity of maximum, minimum and mean initial storage volumes to the limitation of l, c and r in all five main clusters, confirmed the accuracy of the limitation of membership functions of initial storage volume. In this paper the membership function of May (month number 8) as the most critical month in which three crops of wheat, barley and sorghum needed water simultaneously was chosen as a sample and was shown in Fig. 8 and 9. Figure 8 showed the initial reservoir storage membership functions as the main clusters. According to Fig. 8, for instance in C_1 the most degree of membership function was equal to 20 MCM; while the least degree of

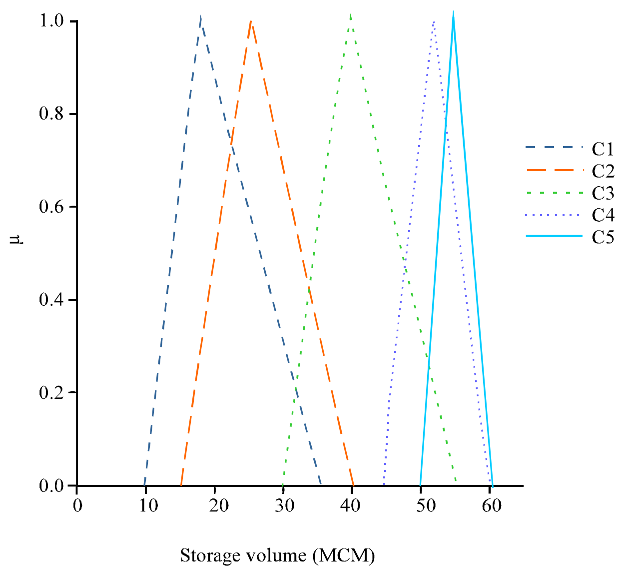

Fig. 8: The membership functions of intial storage volume in five main clusters (C_1 to C_5) in May

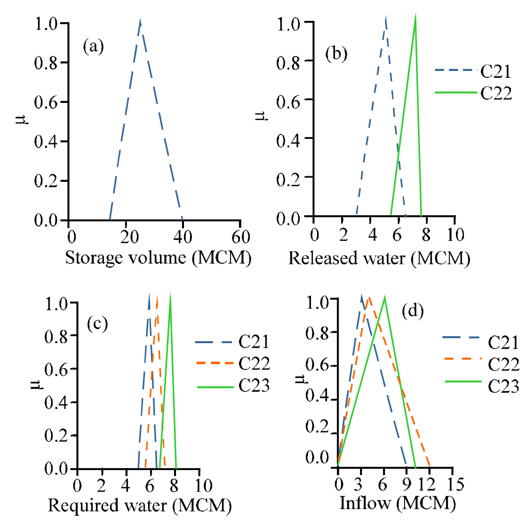

Fig. 9: The membership functions of (a) storage volume (b) reservoir release (c) agricultural demand and (d) river inflow in each cluster in May

membership functions was 10 and 35 MCM. However, the degree of membership function for 15 MCM corresponded to the value of 0.5. Figure 9a represented the second main cluster, i.e., the initial storage volume was 0.25-full at the beginning of the cropping season. The membership function of release, demand and inflow as the sub-cluster of the second main cluster with initial storage volume of 0.25-full at the beginning of the cropping season were shown in Fig. 9b, c and d.

Fuzzy rule base and making decision for reservoir release: As stated previously, each of five main clusters had three sub-clusters. Each sub-cluster had its own rule. Therefore, for each month,

Table 3: Assessment of the fuzzy logic model in both training and test stage

	Training		Testing	
Month	[a]MAE	[b]RMSE	MAE	RMSE
October	0.154	0.195	0.173	0.210
November	0.098	0.172	0.108	0.188
March	0.084	0.109	0.089	0.1189
April	0.35	0.43	0.33	0.435
May	0.83	0.91	0.83	0.92
June	0.66	0.77	0.73	0.84
July	0.61	0.69	0.63	0.71
August	0.85	0.91	0.84	0.91
September	0.81	0.85	0.84	0.87

[a]Mean absolute error, [b]Root mean square error

a total of 15 rules were made. For instance, based on one of the rules obtained for May, if all variables of reservoir storage, inflow and demand were “high”, then the release would be “high”, so the decision making was rather “easy”. On the other hand, if the reservoir initial storage in May 2was “low” and both inflow and demand were “medium”, then the release volume would be “medium”. So, making decision in this condition was more “complicated” than the former one.

Monthly reservoir releases of Fuzzy model were less than those of non-linear programming (Table 3). However, both models followed similar pattern. Although the amount of released water in Fuzzy model was less than Non-Linear Programming, particularly in months with more water demands (for example in May and June when there was a competition between all 3 crops for water, the percentage of water deficit to the percentage of annual mean water deficit were respectively 0.57 and 0.81 in training and 0.93 and 1.145 in the test stage and in summer when Sorghum was irrigated this ratio were respectively 3.42, 0.55 and 2.53 in training and 1.45, 0.97 and 3.37 in test stage), it could not be used as an index for economic performance of the Fuzzy model. Because in this study there was no direct relationship between release volume and Net Benefit in objective function as the economic purpose.

Figure 10 and the two regression lines showed that by increasing the release, the difference between Fuzzy and non-linear programming becomes more. So, what we deduced was in months with more water demands, the difference of released water between two models was more. Since stated before, the period between Decembers up to the end of February was neglected in Fig. 10 because of the period of dormant season.

As Table 3 shows, the highest difference between NLP and Fuzzy models occurred in summer (where Sorghum was irrigated) such that the percentage of water deficit to the percentage of annual mean water deficit were respectively in the months of summer and then for May and June. It should be noted that the results obtained in the test stage were better than training one.

Fuzzy model in different stages of growth: To investigate the efficiency of Fuzzy model and also the Benefit taken by Fuzzy model and the effect of decision variable on net benefit, it was necessary to have insightful study on three crops separately. It should be noted that in Fuzzy model the amount of released water was estimated directly and then based on required and released water, the yield production and net benefit were gained from it. Since the amount of area was determined by NLP in the previous step, the efficiency of Fuzzy model was merely based on released water and yield production of each crop.

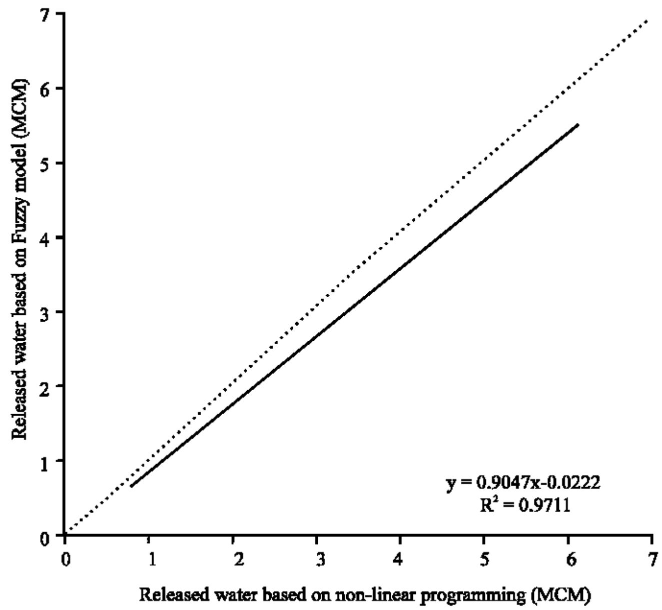

Fig. 10: Comparison of mean monthly release using NLP and Fuzzy model with 1:1 line (Dotted line: x = y, Straight line: Data in both models)

According to the Fig. 11a-e, the amount of monthly released water in all areas of NLP model followed almost the same trend in comparison with Fuzzy model. Over the 12 months period, these Figures had risen from October to May but since then the Figures had fallen gradually. The same trend of Fuzzy and NLP models emphasized that in different states of initial storage volume, average of released water of all states of area had no restriction.

Comparing 3 crops in different stages of growth revealed that in the second half of May as the third stage of the growth of wheat and barley, the YAP_3 played the effective role in total yield production and the net benefit. However, in this period as the first stage of the growth of sorghum, YAP_1 is not so effective. We inferred that even with the maximum yield production of sorghum and its benefit; the highest benefit could not be achievable.

According to the Fig. 12a, the released water in the first stage of growth of wheat in Fuzzy model as an optimum model was more than NLP model but the increase of release in the first stage of their growth had no effect on increase or decrease of Yield production in all 4 states of area. While in the third and fourth stage of growth the less water release resulted into the less Yield production and the differences between two models led to more decrease of yield production and vice versa. In the second stage of growth that relates to the last 10 days of March, the whole April and the first half of May took different results. Decrease and increase of released water for wheat caused a decrease and increase in the yield production, respectively. But the effect of water decrease was much more than water increase.

The results taken from Barley Fig. 12b indicated that decreasing of released water had no effect on the efficiency of Fuzzy model versus NLP, however, the effect of decreasing of water release on dropping the Yield production in the fourth stage of growth compared with other stages was much more.

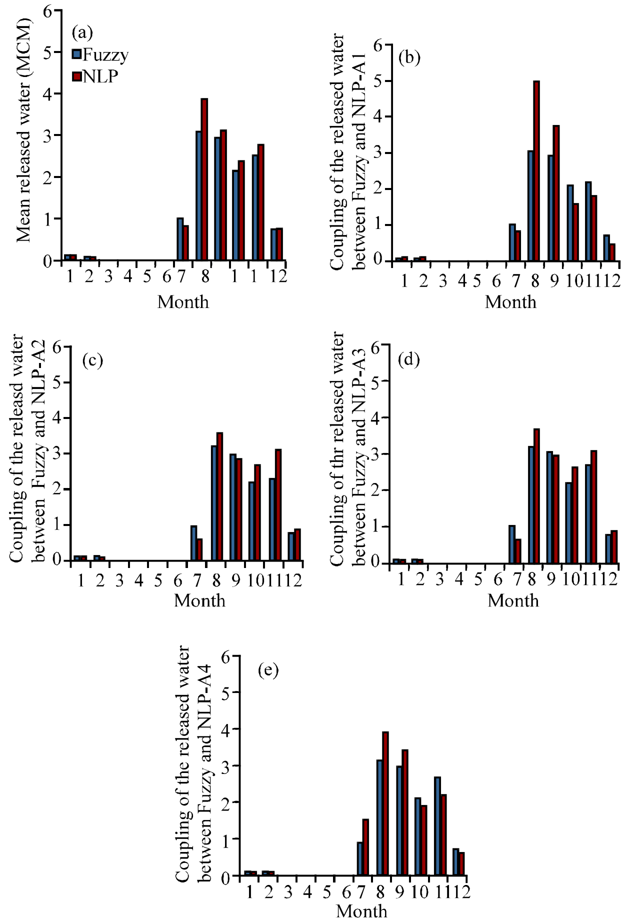

Fig. 11: Comparison of average released water trend in fuzzy model versus NLP in 5 different ststes of area (a) without separating the areas (b) A_1 (c) A_2 (d) A_3 (e) A_4. The areas explained in Table 2

Figure 12c showed that any changes in release made no trends in the yield production of Sorghum except in the first stage of growth that the increase of water releases in contrast to water decrease was more sensible. But in general, there were no definite results in increasing or decreasing of water in different stages of growth.

Fuzzy model vs. NLP in terms of different cultivation area scenarios: According to the Fig. 13, the changing percentage of yield production of wheat and barley compared with sorghum in the first state of area led into less Net Benefit. It should be noted that although the allocated area of wheat was more than sorghum, it could not affect to the net benefit. That means the effect of yield production outweighs of the area.

In the third state of area in which the best results were taken for yield production (the yield production of wheat and barley and sorghum were much closer to the ideal points) the maximum of net benefit was gained.

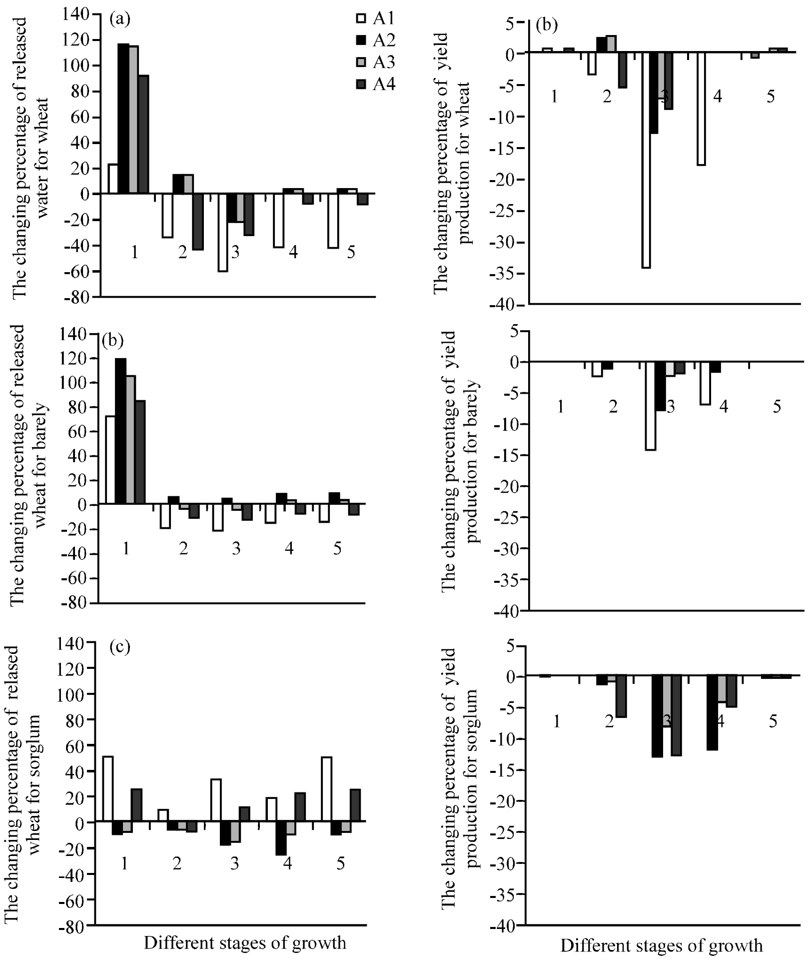

Fig. 12: Changing percentage right: yield production, left: released water in different stages of growth for 3 cultivated crop (a) Wheat (b) Barley and (c) Sorghum

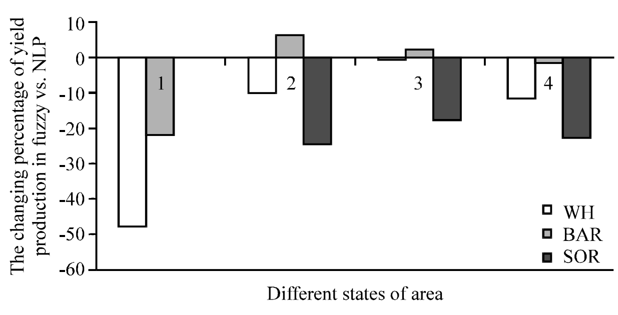

Fig. 13: Changing percentage of yield production for 3 cultivated crops under 4 different states of area

DISCUSSION

In this study the irrigation reservoir operation was considered in two level of decision making including reservoir level and farm level in the North of Khorasan. In reservoir level at the beginning of growing season with 5 states of initial storage volume in a certain period of time two models called Non-Linear Programming and Fuzzy models were run. In Fuzzy model an approach was used based on clustering to make fewer rules with great importance. Clustering of input-output data taken from NLP as input data to Fuzzy system with 15 clusters and 15 Fuzzy rules were investigated. Because of simplicity and calculation speed of clustering, in making Fuzzy rules with the large amount of input- output sets this approach can be replaced with common ones in optimized Fuzzy systems.

Since the mathematical models like Non-Linear Programming cannot present different output in all conditions and different states of input and absolute optimal outputs have differences to a great degree, Fuzzy model as a good replacement was used in making decision as general in future. Results showed that the changing trend of releasing of the reservoir in both models was the same but in general the amount of annual releasing in Fuzzy model was less than NLP. In both model in competitive month (May) releasing was the most and March had the least releasing as Wheat and Barley needed the least water.

In addition, the water deficit in comparison with the amount of cultivated crops acreage played more effective role on net benefit and in the year with water deficit the amount of water released in competitive months should be more considered. To increase the net benefit, we should pay more attention to each crop separately in competitive month (May and June). In the first half of May when only wheat and barley were cultivated, wheat had more effect on net benefit (whether it would be faced with water deficit or not). More consideration on results showed that allocating less water to wheat had significant effect on the yield production of the crop compared with others. Therefore, in the years with much more deficit wheat must take into consideration much more in comparison with other crops, particularly in the second stage of growth. Moreover, in this period for sorghum that passed the first stage of growth, the water deficit had no effects on sorghum's yield production that showed the preference of water for wheat and barley in this period.

Similarly, Irrigation regimes on wheat productivity and water use efficiency in arid conditions in Al-Barrak (2006) study showed that there was a direct relationship between irrigation regimes with grain yields/ha that is the grain yields was significantly increased as the water increased.

According to Reddy and Kumar (2007), a reservoir operation model was developed for irrigation of multiple crops. EMPSO technique was used for optimal utilization of available water resources to maximize the relative yield. The main difference of Reddy and Kumar's study with the present study is that the model performance is evaluated for two types of objective functions, OF_1 and OF_2. The first objective function maximizes the total relative yield of multiple crops, without considering the economic benefit. The second objective function (OF_2), in addition, considers the value of equivalent benefit coefficient (B_c), i.e., the model objective function integrates area-related economic benefits with crop growth sensitivity. In contrast, in the present study relative yield of multiple crops along with area-related economic benefits have been considered in one equation. In both study wheat is a sensitive crop particularly throughout its growth periods. That is mean in Reddy and Kumar's study OF_2 model gives maximum preference for wheat throughout its growth periods and allocates deficits to other crops.

Comparing the results from this study with Mousavi *et al.* (2007) in which the objective function had been presented in other forms indicated the allocation of released water in this study in two steps, reservoir level and farm level, would be more obvious for operator. In study of

Mousavi *et al.* (2007) making decision for releasing was based on objective function with minimum loss unit while in present study addition to making decision for monthly released water, allocation of water to the crops based on their growth sensitivity had been also considered. It means that for example a unit loss in different month had no the same meaning and depends on the crop and the stage of its growth may be different.

Although the objective function in this study was the same as Ghahraman and Sepaskhah (2002), the NLP model was used to maximize the sum of all crop net benefits as an intra-seasonal model for allocation decision. Furthermore, they used a SDP model for making decisions over the seasons of a year resulting in the maximization of expected economic system performance. The results of module I and the seasonal transition probabilities of river inflow and those of rainfall form the inputs to this module. Considering initial reservoir storage class drew different conclusion from the present study. That is mean; the amount of water released in a special month is nearly independent of initial storage volume such that it has almost identical results in different initial storage volumes. In other words, initial reservoir storage class has no effect on net benefit but results taken by Ghahraman and Sepaskhah (2002) showed that net benefit is sensitive to some classes of initial reservoir storage class.

In addition, the structure of thinking to eliminate the linguistic rules by clustering the data into different groups is somehow similar to Sivapragasam *et al.* (2007) what distinguishes present study from Sivapragasam *et al.* (2007) is the kind of clustering method. Also, use of sub-cluster along with main cluster is another difference in both studies. Since the choice of clusters and how the structure of clustering depends on the accuracy desired, it seems to be suitable considering the membership function of reservoir storage volume in each month as main cluster, where each cluster had three sub-clusters including specified river inflow, demand and release for the present case study whereas in the other study all variables were classified in different main cluster. Both study with somehow differences in terms of the structure of clustering results in highly condensed and meaningful rules.

In this study the efficiency of Fuzzy model in contrast to NLP in all states of area was smaller. Since the results from NLP as a mathematical model were absolute, the results from Fuzzy model fewer than NLP were closer to the reality.

Another point is that the fewer released water by Fuzzy model versus NLP does not mean the better efficiency of it and it must be analyzed by objective function of NLP to know how the efficiency of the Fuzzy model is (Hosseinpourtehrani *et al.*, 2011).

ACKNOWLEDGMENTS

The authors are grateful for Dr. Davary for his helpful and constructive comments.

REFERENCES

Al-Barrak, K.M., 2006. Water use efficiency in wheat grown under drought conditions. J. Boil. Sci., 6: 408-411.

Azamathulla, H.M., F.C. Wu, A.A. Ghani, S.M. Narulkar, N.A. Zakaria and C.K. Chang, 2008. Comparison between genetic algorithm and linear programming approach for real time operation. J. Hydro Environ. Res., 2: 172-181.

Borhani, D.A.R. and J.E. Eftekhar, 2005. Assessment of inflow forecast uncertanity in optimal reservoir operation. Iran-Water Resour. Res., 1: 1-15.

Dastorani, M.T., H. Afkhami, H. Sharifidarani and M. Dastorani, 2010. Application of ANN and ANFIS models on dryland precipitation prediction (case study: Yazd in Central Iran). J. Applied Sci., 10: 2387-2394.

Depic, O. and S.P. Simonovic, 2000. Aggregation operators for soft decision making in water resources. Fuzzy Sets Syst., 115: 11-33.

Doorenbos, J., A.H. Kassam and C.I.M. Bentvelsen, 1979. Yield Response to Water. FAO, Rome, pp: 193.

Dubovin, T., A. Jolma and E. Turunen, 2002. Fuzzy model for real-time reservoir operation. J. Water Resour. Plng. Manage., 128: 66-73.

Ghahraman, B. and A.R. Sepaskhah, 1999. Use of different irrigation water deficit scheme for economic operation of a reservoir. Iran. J. Sci. Tech., 23: 83-90.

Ghahraman, B. and A.R. Sepaskhah, 2002. Optimal allocation of water from a single purpose reservoir to an irrigation project with pre-determined multiple cropping patterns. Irrig. Sci., 21: 127-137.

Ghahraman, B. and A.R. Sepaskhah, 2004. Linear and non-linear optimization models for allocation of limited water supply. Irrigation Drainage, 53: 39-54.

Hasebe, M. and Y. Nagayama, 2002. Reservoir operation using the neural network and Fuzzy systems for dam control and operation support. Adv. Engng. Software, 33: 245-260.

Hosseinpourtehrani, M., B. Ghahraman and K. Davary, 2009. Simulation of annual and monthly rainfall with short-term statistical period and high coefficient of variation (Case study: East-West of Dargaz). J. Water Soil Conserv., 16: 153-160.

Hosseinpourtehrani, M., B. Ghahraman, K. Davary and H. Ansari, 2011. Reservoir operating using Fuzzy inference system and clustering (Case study: Ilanjogh Dam). J. Water Soil Conserv.,

Kangrang, A. and S. Compliew, 2010. An application of linear programming model for planning dry-seasonal irrigation system. Trends Applied Sciences Res., 5: 64-70.

Labadie, J.W., 2004. Optimal operation of multi reservoir systems: State-of-the-art review. J. Water Plan. Manage., 130: 93-111.

Mousavi, S.J., K. Ponnambalam and F. Karray, 2005. Reservoir operation using a dynamic programming Fuzzy rule–based approach. J. Water Resour. Manage., 19: 655-672.

Mousavi, S.J., K. Ponnambalam and F. Karray, 2007. Inferring operating rules for reservoir operations using Fuzzy regression and ANFIS. Fuzzy Set Syst., 158: 1064-1082.

Mpallas, L., C. Tzimopoulos and C. Evangelides, 2011. Comparison between neural networks and adaptive neuro-Fuzzy inference system in modeling lake kerkini water level fluctuation lake management using artificial intelligence. J. Environ. Sci. Technol., 4: 366-376.

Mujumdar, P.P. and S. Narulkar, 1992. Optimisation models for multireservoir planning and operation. Hydrol. Rev., 8: 29-52.

Mujumdar, P.P. and T.S.V. Ramesh, 1997. Real time reservoir operation for irrigation. J. Water Resourc. Res., 33: 1157-1164.

Panigrahi, D.P. and P.P. Mujumdar, 2000. Reservoir operation modelling with Fuzzy logic. Water Resour. Res., 14: 89-109.

Ponnambalam, K., S.J. Mousavi and F. Karray, 2001. Regulation of great lakes reservoir systems by a neuro-Fuzzy optimization model. Int. J. Comput. Anticip. Syst., 9: 273-285.

Rani, D. and M.M. Moreira, 2010. Simulation-optimization modeling: A survey and potential application in reservoir systems operation. Water Resour. Manage., 24: 1107-1138.

Reddy, J.M. and N.D. Kumar, 2007. Optimal reservoir operation for irrigation of multiple crops using elitist mutated particle swarm optimization. Hydrol. Sci. J., 52: 686-701.

Reddy, J.M. and N.D. Kumar, 2008. Evolving strategies for crop planning and operation of irrigation reservoir system using multi-objective differential evolution. Irrigation Sci, 26: 177-190.

Russel, S.O. and P.E. Campbell, 1996. Reservoir operating rules with Fuzzy programming. J. Water Resour. Plan. Manage., 122: 165-170.

Shamkoueyan, H., B. Ghahraman, K. Davari and M. Sarmad, 2009. Flood frequency analysis using linear moment and flood index method in Khorasan Provinces. J. Water Soil, 23: 31-43.

Shrestha, B.P., L. Duckstein and E.Z. Stakhiv, 1996. Fuzzy rule based modeling of reservoir operation. J. Water Resour. Plann. Manage., 122: 262-269.

Simonovic, S.P., 1992. Reservoir systems analysis: Closing the gap between theory and practice. J. Water Resour. Plann. Manage., 118: 262-280.

Sivapragasam, C., G. Vasudevan, P. Vincent, P. Sugendran, M. Marimuthtt and S. Seenivasakan, 2007. Rule reduction in Fuzzy logic for better interpretability in reservoir operation. Hydrol. Process., 21: 2835-2844.

Tareghian, R. and S.M. Kashefipour, 2007. Application of Fuzzy systems and artificial neural networks for flood forecasting. J. Applied Sci., 7: 3451-3459.

Teegavarapu, R.S.V. and S.P. Simonovic, 1999. Modeling uncertainty in reservoir loss functions using Fuzzy sets. Water Resour. Res., 35: 2815-2823.

Tilmant, A., M. Vanclooster, L. Duckestein and E. Persoons, 2002. Comparison of Fuzzy and non-Fuzzy optimal reservoir operating policies. J. Water Resour. Plann. Manage., 128: 390-398.

Vedula, S. and P.P. Mujumdar, 1992. Optimal reservoir operation for irrigation for multiple crops. Water Resour. Res., 28: 1-9.

Vedula, S. and D.N. Kumar, 1996. An integrated model for optimal reservoir operation for irrigation of multiple crops. Water Resour. Res., 32: 1101-1108.