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Consideration of Climate Conditions in Reservoir Operation Using Fuzzy Inference System (FIS)

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Authors' contributions

This work was carried out in collaboration between all authors. Author HRS wrote the protocol, designed the study, supervised the research, reviewed and edited the manuscript. Author MAA performed the third stage of the research, managed the analyses of the study and the conclusion and wrote the first draft of the manuscript. Author MHG managed the literature searches, performed the first and second stages of the research. All authors read and approved the final manuscript.

Research Article

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ABSTRACT

In this paper, the Fuzzy Inference System is used for developing an operation model for the Zayandeh-Rud Dam and for planning downstream agricultural crop farms under different climatic conditions. The model consists of three stages: in the first, the storage volume of the reservoir in March is predicted based on both the inflow into the reservoir during the last three months and the Southern Oscillation Index (SOI) using the Adaptive Network-based Fuzzy Inference System (ANFIS). The second stage involves forecasting the annual release in the following year as the model output using both the reservoir storage in the last month of the previous year and the amount of Snow Water Equivalent (SWE) as FIS inputs. As the annual release from the reservoir has definitive effects on the cropping schedule, it may be regarded as a defining factor for climate conditions. The optimized planning of crops for the following year is developed based on the annual release from the dam as forecasted by the fuzzy rules in the third stage of the model. Comparison of observed data and FIS estimations shows that the method developed here is capable of making reasonable decisions about land use and improved crop

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patterns based on climate conditions. The results also show that the Mean Average Error (MAE) for calculating the water demand is lower than 4.0 percent and, further, that in the case of predicting the cropping area, this error is lower than 2.0 percent.

Keywords: Fuzzy inference system; reservoir operation; southern oscillation index (SOI); crop planning.

1. INTRODUCTION

Proper utilization of water resources is an essential task in semi-arid areas like Iran. Reservoirs in such areas will be capable of supplying the water requirements throughout the year, especially in drought periods, by storing the excess water in wet seasons. They also serve as hydroelectric power generation sites, fishing resources, and recreational resorts. In recent decades, reservoir management has become a fundamental problem in water resources management. Researchers have devoted their work to planning reservoir operation based on a multitude of methods. The most important aspect that must be considered in modeling reservoir operation is uncertainty in hydrological events. To take account of such uncertain and random properties, most simulation and optimization methods used for this purpose have been based on stochastic concepts. Yeh [1] presented the state of the art and discussed in detail various models for reservoir operation. Simonovic [2] discussed the limitations in reservoir operation models and remedial measures to make them more acceptable to operators. Russel and Campbell [3] emphasized the ‘high degree of abstraction’ required for the efficient application of optimization techniques.

Uncertainty is an inherent property of most hydrological variation approaches which has motivated researchers to use stochastic or statistical methods in reservoir operation. Stochastic concepts have been recently used for extending the models to produce the widely used ‘Stochastic Dynamic Programming’ (SDP) [4]. Managers and reservoir operators, however, are uncomfortable with the sophisticated optimization techniques used in the models, which have now been made even more complex by including the stochastic concepts related to hydrologic variables. The fuzzy logic approach may provide a promising alternative to these methods because the approach is more flexible, allows for expert opinions to be incorporated into the model developed, and makes it even more appealing to operators, as Russel and Campbell [3] maintained. It must, however, be remembered that although inflow to the reservoir is a continuous variable, only discrete transitions between states of this variable are allowed within the framework of SDP model. Mousavi et al. [5] used the fuzzy set theory (FST) to deal with errors associated with the discretization of variables in an SDP model. Chang et al. [6] used Multipurpose Fuzzy Programming (MFP) for considering the optimization methods in operating a reservoir and the use of water on the downstream land. Liu and Odanaka [7] used the Dynamic Fuzzy Criterion (DFC) model for optimizing reservoir operation. Their goal was to achieve the best operation for meeting all of the water requirements. Bender and Simonovic [8] used the Fuzzy Compromise Method to model the operation based on hydrologic uncertainties. They verified their method for the Tisza River in Poland against the ELECTRE method and obtained good results.

Among the fuzzy methods, the fuzzy rule-based models have been used to derive ‘if-then’ operating rules. The “if” part contains a vector of fuzzy or crisp explanatory variables called premise variables that include inflow, storage, and demand; the “then” part is a fuzzy or crisp consequence like the amount of water released from the reservoir. Many studies have been conducted using this approach. Sugeno simulated the discharge of the Deniper River by using data from its upstream river, the Niman [9]. Dubrovin et al. [10] established a fuzzy rule method named 'Total Fuzzy Similarity' to model the operation of a multipurpose reservoir. Jamali et al. [11] used the Fuzzy Inference System (FIS) for modeling the operation of the Zayandeh-Rud Dam.

A problem commonly faced by managers and stakeholders is the change of climatic conditions and its influence on their decisions. It will, therefore, be useful for managers to be able to model the effects of climate change on water supply decisions. Safavi and Alijanian [12] modeled optimized cropping pattern and irrigation program based on the annual release from the Zayandeh-Rud Dam.

Availability of historical databases of hydrological variations plays an essential role in the simulation and optimization of water quantities, especially when Artificial Neural Networks (ANN) are to be used, whose most important capability is making predictions based on such database. ANN is now being widely employed not only for river stage and rainfall forecasting but also for deriving river operating policies[13-20]. FIS and ANN have been combined to develop a new approach called 'Adaptive Network-based Fuzzy Inference System' (ANFIS). The new method has been widely used for deriving reservoir operation models as it has the advantages of both ANN and the Fuzzy-Ruled methods. In ANFIS, ANN is used for developing the fuzzy rules. Alternatively, other methods such as Genetic Algorithm (GA) may be used for this purpose. For example, Ozger [21] developed the fuzzy rules by GA and predicted the flow of the Euphrates River in Turkey. He also compared his results with those obtained from an ANFIS model.

In this paper, the Fuzzy Inference System is used to develop a model for the operation of the Zayandeh-Rud Dam and for planning downstream crop farms under different climate conditions. The model consists of three stages. In the first, the storage volume of the reservoir in March is predicted based on both the inflow into the reservoir during the last three months and the Southern Oscillation Index (SOI) using the Adaptive Network Fuzzy Inference Systems (ANFIS). The second stage involves forecasting the annual release in the following year as the model output using both the reservoir storage in the last month of the previous year and the amount of Snow Water Equivalent (SWE) as FIS inputs. As the annual release from the reservoir has definitive effects on the cropping schedule, it may be regarded as a defining factor for climate conditions. The optimized planning of crops for the following year is developed based on the annual release from the dam as forecasted by the fuzzy rules in the third stage of the model. Data from 1990 to 2006 are used in developing the model.

2. STUDY AREA AND DATABASES

The proposed approach was used for modeling the operation of the Zayandeh-Rud Dam reservoir erected on the Zayandeh-Rud River flowing in the Zayandeh-Rud basin in Isfahan Province, Iran (Fig. 1).

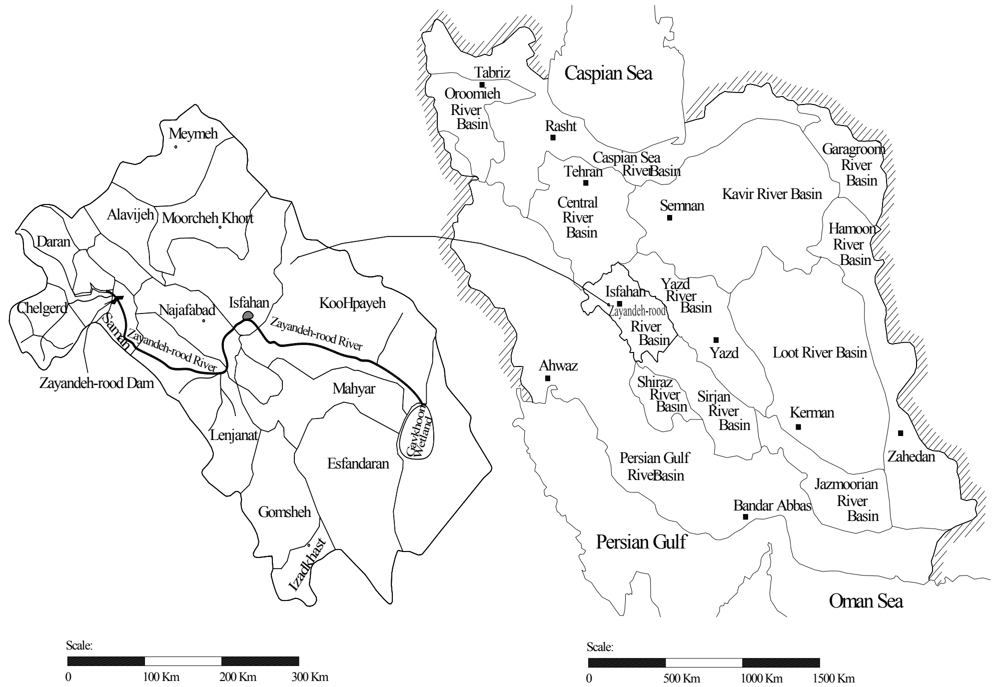


Fig. 1. The Zayandeh-Rud River Basin

The reservoir operated since 1971 is a multipurpose one used for hydropower generation, flood control, and irrigation as well as for maintaining environmental flows. Irrigation needs accounts for the greatest demand (about 85% of the total water demands in the basin). According to Iranian hydrological classification, the Zayandeh-Rud is the only perennial river in central Iran, which is part of Esfahan and Sirjan Catchment located in Iran's central plateau. The river plays an important role in the livelihood of the inhabitants along its course where the major crops grown are wheat, rice, corn, potato, and various fruits [22]. The growing period for each crop in the Zayandeh-Rud basin is shown in Fig. 2.

Both the surface water released from the Zayandeh-Rud River and the groundwater in the basin are used for irrigation of an area of around 100,000 ha downstream the Zayandeh-Rud Dam. Most crops in this area are cultivated in the spring and summer. The annual irrigation water demands range from a maximum of 2884.63 to a minimum of 1315.05 Million Cubic Meters (MCM), 60% to 80% (or an average of 70%) of which is supplied by the water released from the reservoir [23].The gross storage capacity of the reservoir is 1470 MCM and its live storage capacity is 1090 MCM. A water year (September 1 to August 31) is divided into 24 fifteen-day periods. Table 1 shows the average inflows, releases, and irrigation demands for the reservoir.

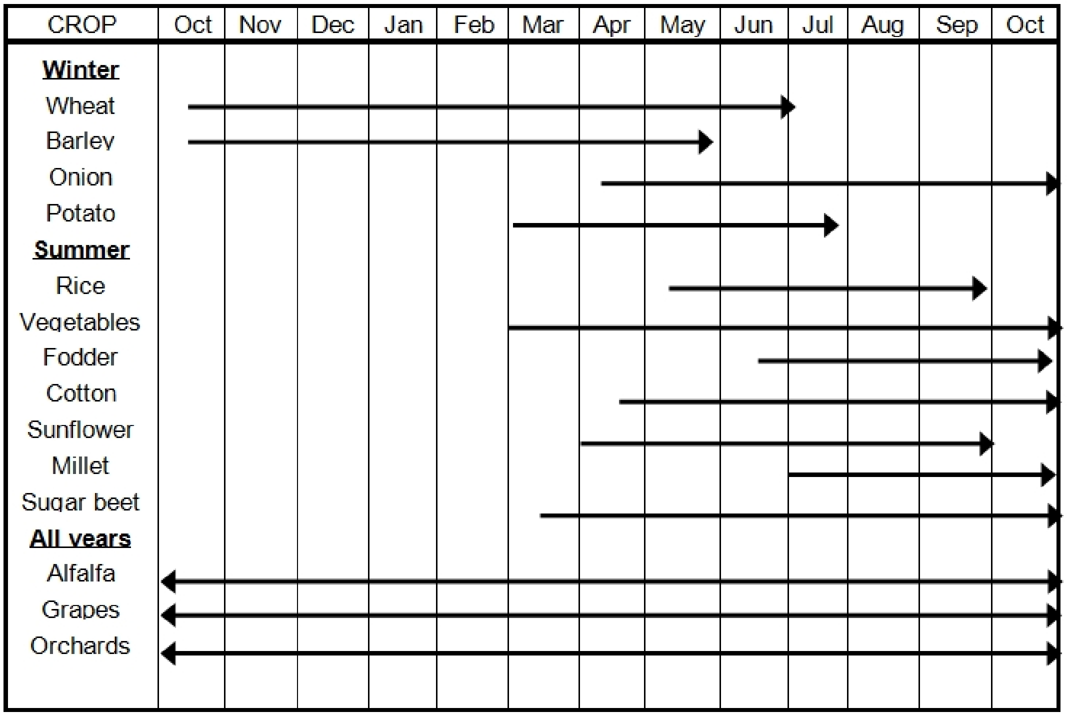


Fig. 2. Typical schedule for crops in the Zayandeh-Rud Basin

Table 1. Average inflows, releases, and irrigation demands of the Zayandeh-Rud Dam

Month	Inflow (MCM)	Release (MCM)	Demand (MCM)
September	39.84624	107.351	129.81
October	56.75656	103.981	77.47
November	65.97583	92.1595	252.02
December	62.81385	46.4865	234.99
January	73.59206	30.9324	30.76
February	142.0152	55.2324	84.37
March	314.7018	138.176	136.08
April	294.3572	204.427	306.64
May	187.2198	193.23	347.13
Jun	119.4994	169.684	298.24
July	72.03527	168.616	238.94
August	44.58766	152.9	183.02
Annual	122.7855	121.9320	193.2891

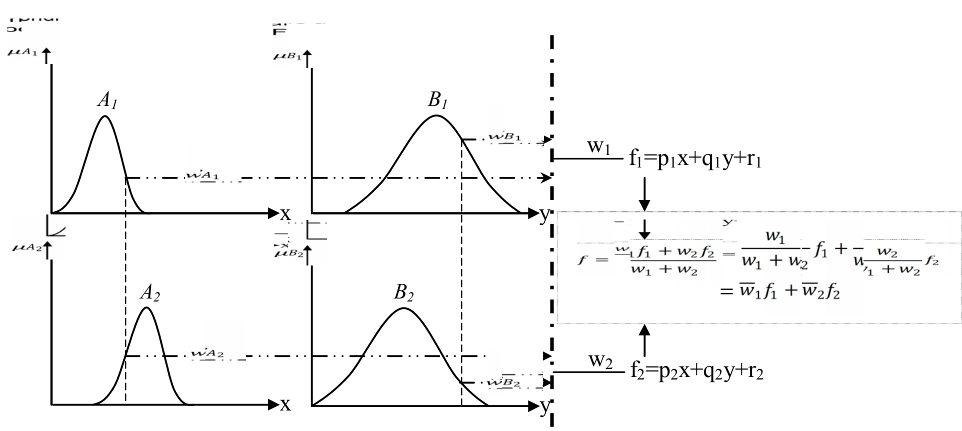
3. METHODOLOGIES

Most systems are characterized by some kind of ambiguity that causes problems in their understanding or in making inferences from them. Linguistic or quality expressions are one source of such ambiguity that poses difficulties in deriving logical senses or quantitative values from them. An example situation is when an expert claims that ‘the rainfall in an area is good’, by which it is hard to understand exactly how much rainfall means good conditions in that area. The fuzzy set theory, expounded by Zadeh [24], is a workable and useful method for resolving these ambiguities. One of the most important features of the fuzzy set theory is its capability to develop rule-based models. Since fuzzy set theory has the ability to work on linguistic variables, the rules based on the knowledge and experience of experts can be incorporated into the models thus developed. According to Sugeno and Yasukawa [25], fuzzy-rule based modeling, which they called Fuzzy Inference System model, is a qualitative modeling scheme where system behavior is described using a natural language. FIS models can make decisions on the basis of experts' experiences, which cannot be tested or trained using a database. Rather, it is on experts develop the rules for these purposes to introduce them into the model. On the other hand, Neural Networks have the capability to work on databases in order to extract the relationship(s) between inputs and outputs via training and testing processes. Jang [26] combined these two advantages into a single system called Adaptive Network-based Fuzzy Inference System (ANFIS). While the system works on linguistic variables to develop if-then rules, it also trains the rules based on the database by using the neural networks. Two different approaches are commonly available for developing the fuzzy rules, namely the Mamdani and the Takagi-Sugeno-Kang (TSK). The differences between these two approaches can be explained as follows [21]:

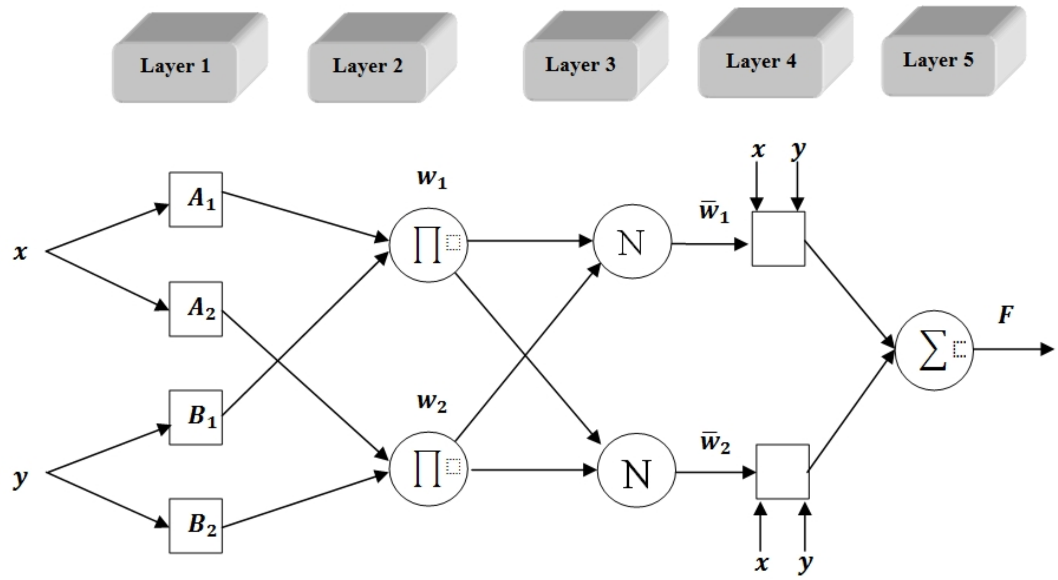
In the case of the Mamdani model, both input and output variables, and for the TSK model, only the input variables, are fuzzified by considering convenient linguistic sub-sets such as high, medium, low; heavy, light; hot, cold; etc.

Rules are constructed based on expert knowledge and/or available data. Expert knowledge can be used only with the Mamdani model. In TSK, however, rules are based on training by ANN. The result appears as a fuzzy set in the Mamdani model and as individual rule outputs in the TSK model. It is, therefore, necessary to defuzzify the set to a numeric value that can be used by the administrator or the engineer. Most often, the defuzzification procedure is achieved through the centroid method in the Mamdani model and the weighted average method in the TSK model, as applied herein [21].

ANFIS model is a TSK-type neuro-fuzzy system which employs the feed forward network. The general structure of the ANFIS is presented in Fig. 3. Selection of the FIS is the major concern when designing an ANFIS to model a specific target system [27]. The corresponding equivalent ANFIS architecture is presented in Fig. (3b).



a)



b)

Fig. 3. (a) Fuzzy inference system (b) Equivalent ANFIS architecture

3.1 Theory/Calculation

In this paper, we follow a three-stage model to describe the operating of the Zayandeh-Rud Dam for cultivation of the downstream lands under diverse climatic conditions. Fig. 4 illustrates the schema of these stages.

In the first stage, an ANFIS model is developed to predict the storage of the reservoir at March. Model inputs include the input volume of the reservoir over the last three months the Southern Oscillation Index (SOI) in the last month while model output will be the storage volume at the April. The data from 1971 to 2004 are used in this model, approximately 64 percent of which is used for training (1971 to 1992) and the remaining for testing and validation of the model (1993 to 2004): 18% for testing and 18% for validation of the selected model.

The second stage of modeling forecasts the annual release representing the model output. For this purpose, it uses the storage volume in the last month obtained in the first stage, and the equivalent water obtained from the snowmelt of that month representing the inputs in this stage. This stage is modeled by ANFIS, too.

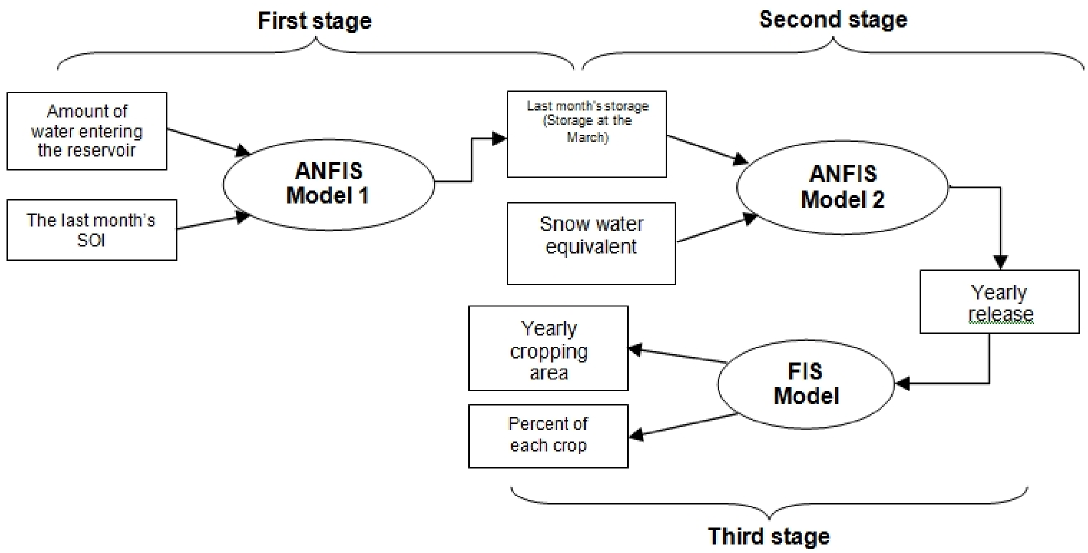


Fig. 4. The schema of the model stages

The statistical period included 1989 to 2004 which was allocated to the training, testing, and validation of the model as described above. Table 2 shows the statistical database used in the ANFIS models of stages 1 and 2. Also, Figs. 5 to 8 illustrate the monthly storage and inflow into the Zayandeh-Rud Dam, SOI, annual release, and annual snow water equivalent for the Zayandeh-Rud Dam.

Table 2. Statistical parameters of the data used in both ANFIS models

Input or output parameters of the models (observed data)	Period	Average	Maximum	Minimum	Variance	Deviation
SOI	1971-2004	-0.2	2	-4.6	2.6	1.61
The input water to the reservoir (MCM)	1971-2004	266.7	490.7	133.8	9476.6	16.33
Storage (MCM)	1971-2004	896.7	1239	198	71816.8	267.99
Snow water Equivalent (cm)	1989-2004	102.5	288.3	11.3	7686.7	87.67
Release (MCM)	1989-2004	1496.4	2543.4	567.5	169967.3	412.27

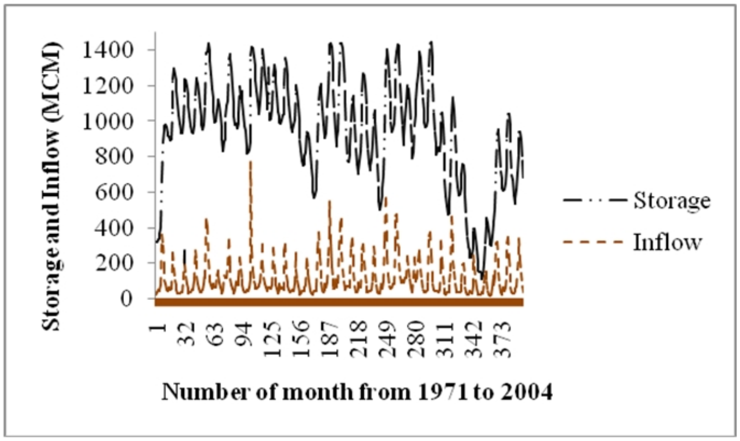


Fig. 5. Monthly storage and inflow of the Zayandeh-Rud Dam

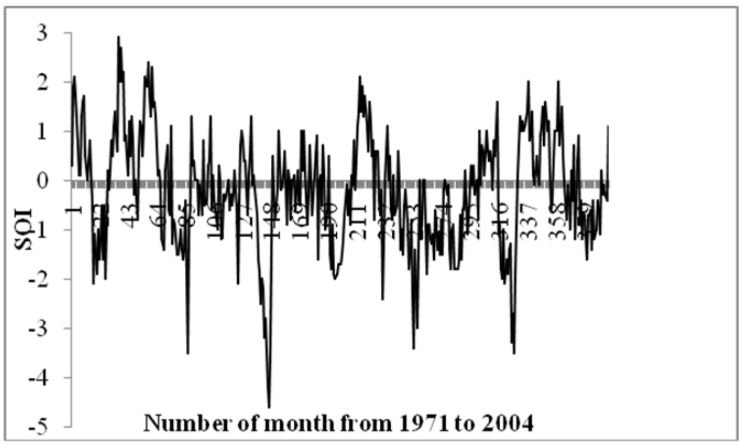


Fig. 6. Southern oscillation index (SOI)

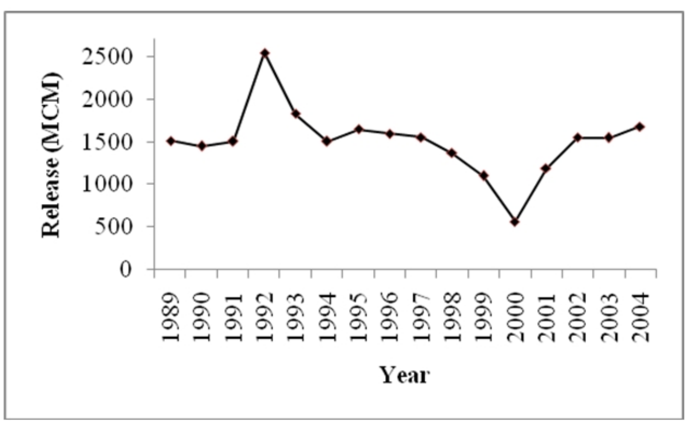


Fig. 7. Annual release from the Zayandeh-Rud Dam

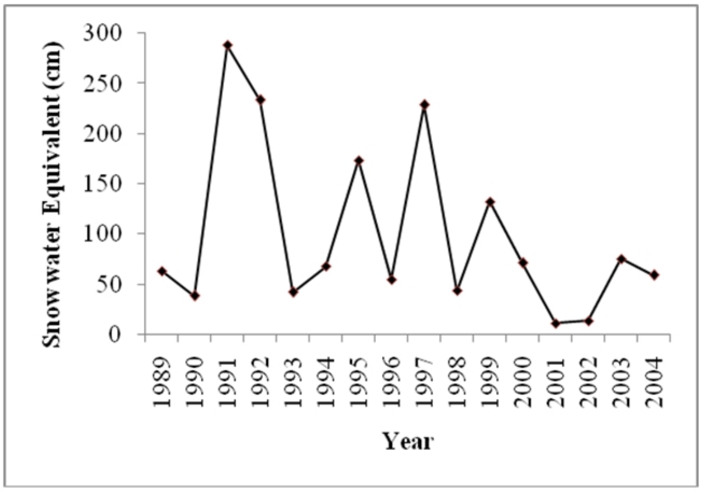


Fig. 8. Annual snow water equivalent (upstream the Dam)

For the purposes of this study, two ANFIS models have been used for the following reasons:

1. **The periods of the available statistical data were not equal:** Statistical data of SOI, the input water to the reservoir, and storage were available for the period from 1971 to 2004; but snow water equivalent and release were available only for the period from 1989 to 2004. Thus, it would not be possible to model these data using a single ANFIS model.

2. **Speeding up the simulation process:** In modeling by ANFIS, if the number of inputs is shown by N and the number of membership functions (MFs) of each input is shown by P, then the number of rules is obtained by PN. If the number of inputs is increased, not only will the simulation speed decrease, but a limited number of membership functions can be used for each input. It follows that the lower the number of inputs, the higher will be the speed of simulation and the more will be the number of membership functions used for each input.

3. **High performance of ANFIS in forecasting:** The high performance of this model in forecasting compared to other models is well proven [27-32].

Performance of the models is evaluated against Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and coefficient of determination (R^2). The MAE measures the average magnitude of the errors in a set of forecasts without considering their direction; it measures accuracy for continuous variables. The RMSE is a quadratic scoring rule which measures the average magnitude of the error. The MAE and the RMSE can be used together to diagnose the variation in the errors in a set of forecasts. The RMSE will always be larger than or equal to MAE; the greater the difference between them, the greater the variance in the individual errors in the sample. If the RMSE=MAE, then all the errors are of the same magnitude. Both MAE and RMSE can range from 0 to ∞. They are negatively-oriented scores: Lower values are better.
The structure of the ANFIS model developed for the first stage with different MFs is presented in Table 3. The model with nine triangular MFs and 500 iterations was the simplest model yielding good results and was, therefore, selected for the first stage.

Table 3. The structure of different models used for the first stage

MF type	Num. of MF	Epoch	Error		
			RMSE	MAE (%)	R^2
Gaussian	9	500	10.75	9.25	0.87
Gaussian	5	1000	11.40	9.00	0.89
Gaussian	7	500	11.36	8.93	0.89
Bell MF	5	1000	17.99	9.73	0.68
Bell MF	7	500	10.70	8.78	0.90
Triangular MF	9	500	9.50	8.24	0.91
Triangular MF	7	500	10.09	8.37	0.92
Triangular MF	5	500	16.47	10.35	0.70
Validation of selected model					
MF type	**Num. of MF**	**Epoch**	**Error**		
			RMSE	**MAE (%)**	**R^2**
Triangular MF	9	500	16.72	16.25	0.72

Table 4 shows the specifications of the different models developed for the second stage. According to the results, the model with five triangular MFs and 500 iterations is the simplest yielding good results.

Table 4. The results of different models used for the second stage

MF type	Num. of MF	Epoch	Error		
			RMSE	MAE (%)	R^2
Gaussian	9	500	9.48	5.27	0.95
Gaussian	7	500	9.47	5.27	0.95
Bell MF	7	500	5.58	4.46	0.98
Triangular MF	5	500	5.34	4.23	0.98
Triangular MF	7	500	6.44	4.03	0.98
Validation of selected model					
MF type	**Num. of MF**	**Epoch**	**Error**		
			RMSE	**MAE (%)**	**R^2**
Triangular MF	7	500	11.15	7.21	0.92

The third stage determines the kinds of crops to cultivate. This model is based on FIS. Based on the rainfall data for the period from 1972 to 2010 obtained from the station upstream the Zayandeh-Rud Dam, it is clear that the study area experiences different climate conditions. While the minimum annual rainfall is around 82.5 mm, its maximum and average values are 367 and 223 mm, respectively. Fig. 9 illustrates the annual rainfall at the Zayandeh-Rud Dam station. The amount of precipitation in wet seasons is around 300 mm but around 120 mm in drought conditions. We may, therefore, conclude that while there are obvious differences in the amount of precipitation under different climate conditions, the total rainfall does not change dramatically under Dry and Wet climates when each one is considered on its own. This means that the amount of rainfall at this station is around 120mm in drought conditions, and it is around 300 mm in wet situations. Focusing on seasonal rainfall, however, we may note changes in the climate conditions in this area. Fig. 10 shows seasonal rainfalls monitored at the Zayandeh-Rud Dam station. Clearly, the winter rainfall (dashed line with triangular signs) follows a steady trend which is less than the maximum and minimum recorded values of 200 mm and around 50 mm, respectively. The amount of rainfall in the fall (cross signs), however, has a decreasing trend from 180 mm to 125 mm, falling within the maximum range. What complicates the situation is the fact that neither the maximum nor the minimum rainfalls occur simultaneously in the same year. For instance, in the years 1980, 1988, 1993, 1996, 2004, and 2006 when rainfall is in its maximum range in winter, it is in its minimum range in the fall of the same year. In addition, the amount of rainfall does not greatly change in spring when it ranges between 75 and 100 mm. When considered on a monthly basis, rainfall in the area during the months of November, December, March, and April is found to have greater values than it has in other months.

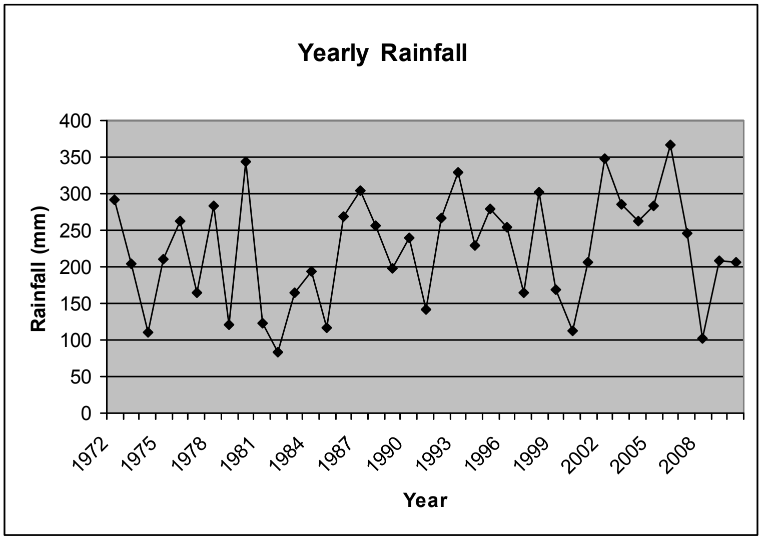


Fig. 9. Annual rainfall

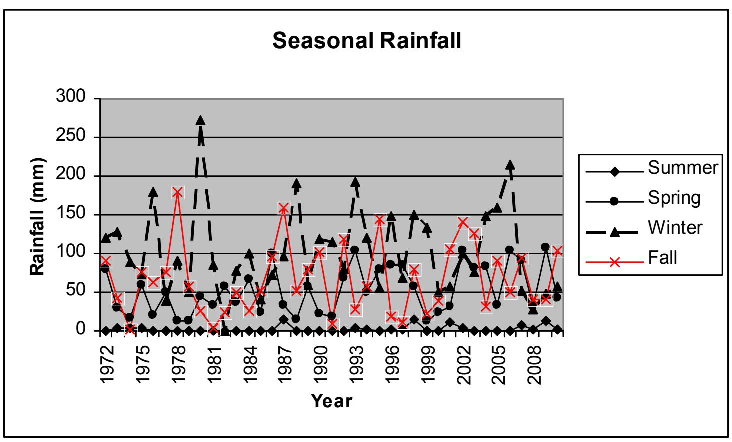


Fig. 10. Seasonal rainfall

Fig. 11 shows the quantities of rainfall recorded at the Zayandeh-Rud Dam station for those months with greater impacts. The points in the figure indicate that not only does the climate of the area change from month to month, but that its impact on the climate conditions in the area also follows an increasing trend.

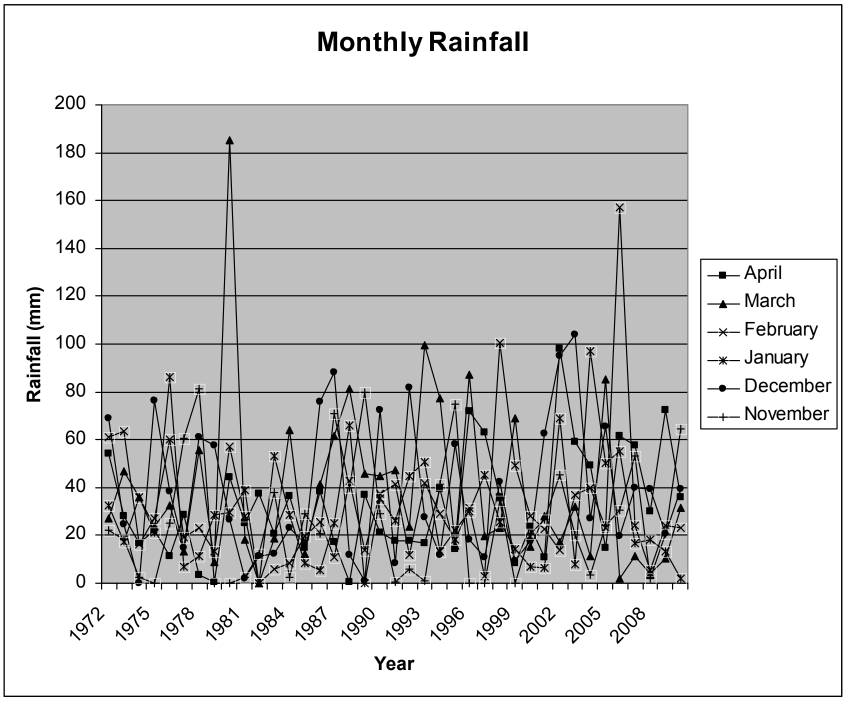


Fig. 11. Monthly rainfall

This state of affairs leads farmers to concentrate on certain crops such as wheat since they naturally adapt their crops and cropping area to predictable climate conditions. If they can predict undesirable weather/climate conditions, they will then plan for crops with lower irrigation requirements and reduce their cropping area. Thus, relationships exist between climate conditions and cropping pattern in the area which are expressed in rules most of which are expressed in linguistic terms and can be stated as If-Then rules by FIS. For example, "If the climate condition is good, farmers will cultivate more rice". Some words such as “good” in these linguistic rules are fuzzy sets that must be quantified by some membership function.

In this paper, the Mamdani approach is used to quantify the input and output membership functions and also to develop the rules governing their relations. The annual release from the Zayandeh-Rud Dam is used as the input for predicting or determining climate or water conditions. The sets range over 500 to 2600 (MCM). Expert views expressed by the manager of the Zayandeh-Rud irrigation system are considered in deriving the membership functions. In order to initialize the fuzzy membership functions, two specific approaches are introduced which draw upon the fuzzy clustering and the expert knowledge methods. While the latter can only be used in Mamdani model, the former is usually used in Takagi-Sugeno-Kang model. On the one hand, an adequate range of data was required for clustering the needs. On the other, qualified and experienced professionals at Isfahan Regional Water Company are in charge of water resources management in the region. The authors, therefore, decided to develop the fuzzy membership functions of the FIS model based on expert knowledge. Further details on this are provided in Safavi and Alijanian [12]. Using this approach, questionnaires were prepared in which experts were asked to define their views of "bad", "normal", and "good" water conditions in Isfahan region. Based on their views, “normal” referred to conditions in which the annual water released was predicted to be about 1350 MCM. The difference between 500 and 1350 MCM was regarded as undesirable, or bad, conditions and when the water released varied from 1350 to 2600 MCM, conditions were regarded as better than “normal”. Since these two intervals are not equal, the divisions by odd membership functions will not be symmetrical. Thus, another division with eight membership functions is compared with divisions having odd membership functions. In this division, the first and the last membership functions are trapezoidal, which are the extensions of two triangular membership functions. Table 5 compares the results of each model with field data and shows that the statistical parameters are better for FIS models with eight membership functions.

Table 5. FIS models with different numbers of membership functions (MFs)

Number of MFs	Interval	R^2	RMSE	MAE
3 MFs	1991 - 2006	0.75	1187	37
5 MFs	1991 - 2006	0.77	1050	32
7 MFs	1991 - 2006	0.78	971	27
9 MFs	1991 - 2006	0.69	1937	49
8 MFs	1991 - 2006	0.88	513	12

Accordingly, the input set is divided into eight different linguistic terms defining water conditions based on annual water release from the Zayandeh-Rud Dam reservoir. These linguistic terms are: “very bad”, “bad”, “fairly bad”, “normal”, “fairly good”, “good”, “very good”, and “excellent”.

The results comprise the total annual cropping area and the farmers’ preference for major crops to be grown. These sets are studied by both considering expert knowledge and analyzing a database of crops covering the period from 1991 to 2006. Thus, the sets are represented by eight fuzzy sets. Fig. 12 shows the MFs for releases from the dam as the input parameter while Figs. 13 and 14 show the cropping area and the percentages of wheat and rice, the two most important crops, as outputs.

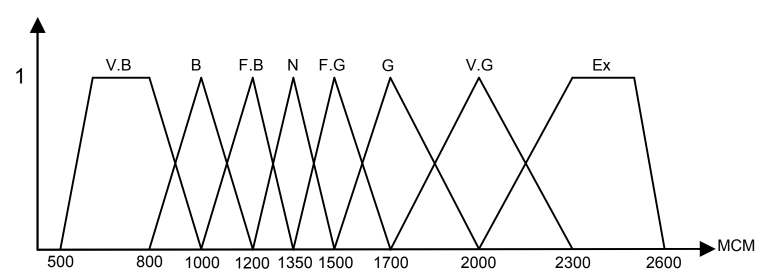


Fig. 12. Climatic conditions in linguistic terms on the basis of estimated yearly water release from the Zayandeh-Rud Dam (MCM)

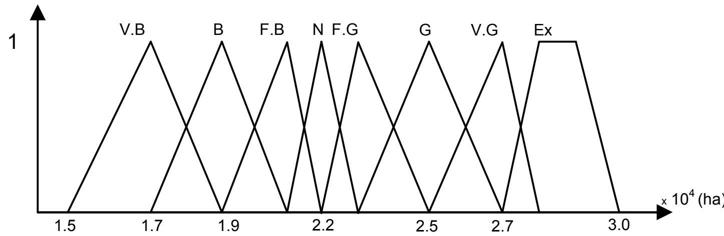


Fig. 13. Cropping area in linguistic terms (ha)

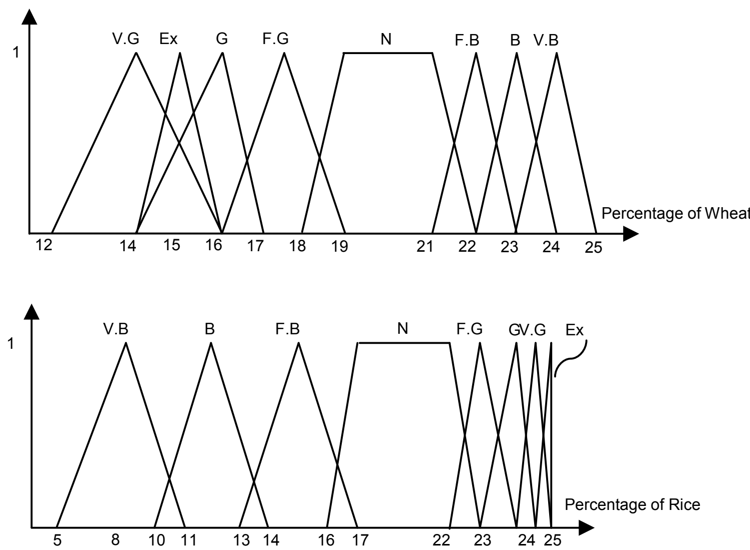


Fig. 14. Cropping area allocated to each of two crops (wheat and rice) in linguistic terms

Table 6 shows the characteristics of each crop. Clearly, some crops, such as wheat, rice and orchards, have fuzzy characteristics and the farmers' preference for growing them is different under different climatic conditions. These characteristics are derived from expert views and the databases available at Isfahan Regional Water Company. This is while farmers show the same tendency to grow other crops and the percent of area allocated to them is the same under different climate conditions. However, we should note that the total cropping area allocated to each crop is different under each climate condition and the effect of climate condition on each crop is accounted for in the total area allocated to that crop.

Table 6. Cropping percent for all crops

Crop	Wheat	Barely	Corn	Rice	Potato	Onion	Green	Provender	Orchards
Percent	Fuzzy	8	4	Fuzzy	7	4	6	12	Fuzzy

Using FIS, we can improve some rules for predicting the total cropping area and the farmers' tendency to grow each crop based on climate conditions. The results of this prediction are different for different releases from the Zayandeh-Rud Dam. The rules governing input and output sets are improved based on these membership functions. For instance, one such rule states that "if the climate condition is "fairly bad" (which is equal to a release between 1000 to 1350 MCM), then the cropping area is "fairly bad" (which is equal to a cropping area between 19000 (ha) and 22000 (ha)). Table 7 shows the results for three different annual releases from the dam (namely, 850, 1550, and 2150 MCM), which are defined as bad, normal, and excellent water conditions, respectively.

Table 7. Results of FIS for predicting cropping area and percent of each crop for different water conditions

Annual release (MCM)	Cropping area (ha)	Cropping percentage of rice	Cropping percentage of wheat	Percentage of orchards
850	17578	21	18.5	29.8
1550	24061	29	16.9	18.3
2150	27615	31.2	14.3	19.2

It may be inferred from these results that if the water conditions get better, the cropping area increases and the farmer’s preference for rice rises but preference for fruits and wheat will decline. One reason for this is the fact that wheat is cultivated in the fall and harvested in the spring. So, based on the change in the climate conditions of the area and the fact that precipitation in the area increases in the months of November, December, March, and April, the farmers would prefer to cultivate wheat in normal conditions. But when the conditions become better, farmers prefer to cultivate rice instead of wheat. This is because the orchard area is nearly constant and preference for orchard fruits, therefore, decreases when the total cropping area increases.

The net irrigation demand of each crop in each month can be calculated. These values are calculated using the FAO-CROPWAT method based on a ten-year average database and by considering the usual growing periods as shown in Fig. 2.

Finally, the total net irrigation demand including all crops can be calculated using the following relation:

$$ND_i = \sum\nolimits_c A \times Per_c \times dc_i \tag{1}$$

where, ND_i is the total monthly net demand, A is the total annual cropping area obtained by the Fuzzy Inference System, Per_c is farmer preference for each crop, and dc_i is the net irrigation demand of each crop in each month calculated by FAO-CROPWAT.

4. RESULTS AND DISCUSSION

In this paper, a three-stage model was used for operating the Zayandeh-Rud Dam to develop an optimized plan for cultivation of downstream farms under diverse climate conditions. The first 2 stages were developed by ANFIS and the 3rd stage was developed by FIS. Two ANFIS models were used because the available periods of statistical data were not equal while it would also speed up the simulation. The output from these two stages of simulation was regarded as the annual release of the reservoir in the next year, representing the input to FIS.

Table 8. Comparison of observed and FIS predicted data

Year	Yearly release of water (MCM)	Cropping area (ha)		Percentage of wheat		Percentage of rice		Percentage of orchard		Demand (MCM)	
		Observed	FIS	Observed	FIS	Observed	FIS	Observed	FIS	Observed	Model
1999-2000	1102.1	21729.3	21057	22.0	22.3	13.6	13.5	25.1	24.5	242.8	226.9
2000-2001	567.5	16737.2	16705	17.2	17.0	8.4	8.0	29.6	30.0	182.3	185.0
2001-2002	1186.7	19617.8	20452	22.5	22.0	15.0	14.7	21.2	24.1	226.3	238.5
2002-2003	1549.4	22232.0	23055	17.5	16.9	24.3	23.1	18.6	18.3	264.8	284.7
2003-2004	1545.4	22964.0	23011	16.9	17.0	22.1	23.1	18.5	18.4	276.0	284.2
2004-2005	1678.1	25049.5	24954	15.1	16.0	23.8	23.7	17.3	18.1	297.2	294.4
2005-2006	1837.6	25719.0	25656	15.1	14.9	23.3	24.0	18.1	17.8	293.2	300.8
R^2		0.97		0.97		0.99		0.94		0.93	
RMSE		512.92		0.46		0.68		4.36		40.05	
MAE		1.72		2.17		3.01		3.73		3.92	

The water demand calculated by Eq. 1 is different for each water condition. Based on this equation, water demand will change in response to changes in cropping area and farmer's preference for each crop. The cropping area and preference for basic crops are different under different climatic conditions. Table 8 shows the values for cropping areas, preferences for basic crops (wheat, rice, and orchard fruits), and water demand. Clearly, cropping area has improved by increasing the amount of water released from the Zayandeh-Rud Dam. On the other hand, by increasing the amount of water released, farmer's preference for the crops with lower irrigation demand (wheat in this case) reduces compared to those with higher water demands (rice in this case). This means that FIS can be used to develop a cropping plan based on changing climate conditions as it takes into account farmers' decisions and that the model can adequately predict farmers' decisions. The last column in Table 8 compares the observed values of annual water demand and the same value calculated by Eq. 1. The comparison shows that the results are sufficiently acceptable. According to this Table, the values for the statistical parameters (R^2, RMSE, and MAE) are acceptable for all the water demand values predicted by FIS and calculated by Eq. 1. For example, the average error, MAE, in calculating the demand is lower than 4.0 percent. These results show that the observed values and their estimations are close to each other. The same can be inferred from the results for observed percentages of three diverse crops (wheat, rice and orchard) and their estimations in the relevant years.

5. CONCLUSION

This paper satisfies two objectives. The first involves simulating the operation of the Zayandeh-Rud Dam in a two-stage process. In the first stage, the inflow into the reservoir during the March is predicted on the basis of the amount of water in the three preceding months and the SOI parameter of the last month. These two values are then used as inputs to an ANFIS model. The second stage consists in developing another ANFIS model whose inputs are the inflow into the reservoir, i.e. the output from the model developed in the first stage, and the amount of snow water equivalent of the last month. The output of the second stage is the annual release for the following year, which is our first objective. The second objective is achieved through a third stage which is meant to develop a cropping schedule by taking into account different climate conditions and their influence on water conditions using expert knowledge and experience. This objective is realized by using FIS. Another corollary of the approach adopted in this paper is the calculation of net monthly water demand by FIS based on the cropping schedule developed.

In this paper, SOI was used for considering climate conditions. Other parameters can be suggested for considering climate conditions and the associated effects on reservoir operation. Also, the conjunctive use of surface and groundwater and their effects on the Zayandeh-Rud Dam operation may be suggested for future study. Another interesting area will be the study of climate change and its effects on reservoir operation using hybrid models and downscaling methods.

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COMPETING INTERESTS

Authors have declared that no competing interests exist.

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