Stream Flow Forecasting and Reservoir Operation Models Using Fuzzy Inference Systems

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Abstract

In this study, a fuzzy inference system is developed for reservoir inflow forecasting and reservoir operation. The system consists of two models. In the first model, the seasonal river stream-flow is forecasted with a fuzzy rule based system. The southern oscillated index, rain, snow, and stream-flow are inputs of the model and the seasonal stream-flow is its output. The second model is a reservoir operation model based on an "If-Then" principle, where "If" is a vector of fuzzy premises and "Then" is fuzzy consequences. The reservoir storage capacity, inflow, demand, and year condition factor are used as the premises and monthly release is taken as the consequence. As a case study, the Zayandeh-Rood Reservoir in Iran is studied. To evaluate the performance of the operation model, different performance criteria such as reliability, resiliency, and vulnerability are calculated. Results indicate that use of this method in extracting knowledge from an informative data set having ill-defined and highly nonlinear structures would be helpful and have advantages over traditional operation methods such as standard operating policy or ordinary least-squared regression rules constructed based on the results of optimization models.

***Keywords*:** Reservoir operation; Fuzzy inference system; Performance criteria; Standard operating policy; Ordinary least-squared regression

1. Introduction

In the past years, Fuzzy Inference System (FIS) has been applied to different subjects. FIS which is based on expertise expressed in terms of 'If-Then' rules can be used to predict uncertain systems and its application does not require knowledge of the underlying physical process as a precondition. Because of the high degree of abstraction necessary for efficient application of optimization techniques, the applicability of most reservoir operation models is limited. The managers and reservoir operators are often uncomfortable with the complicated optimization techniques used in the models, which are made much more complex because of the stochastic nature of the hydrologic variables. The fuzzy logic approach may provide a promising alternative to the traditional optimization methods used for reservoir operation modeling.

The concept of fuzzy set theory was established by L. A. Zadeh (1965). He used this theory in modeling of uncertainty at decision making. Of the several approaches used to apply fuzzy set theory to reservoir operation, fuzzy optimization techniques, fuzzy rule based systems, and combinations of the fuzzy approach with other techniques are more popular. Fuzzy rule based control systems for reservoir operation was presented by Russell and Campbell (1996) and Shrestha et al. (1996). Studies of Russell and Campbell indicated that the fuzzy approach is more flexible and allows incorporation of expert opinions, which could make it more acceptable to operators. Shrestha et al. also verified that fuzzy logic is an appropriate tool to consider the inaccuracy of variables, like inflows in reservoir operation modeling. Fontane et al. (1997) also dealt with the imprecise nature of objectives in reservoir operation modeling. Jolma et al. (2001) used a fuzzy logic based approach to model the operation of a system that consists of five lakes. Their attempt was based on expert knowledge and on water level and release data. The goal of the modeling was to mimic the human operator. Dubrovin et al. (2002) constructed a fuzzy rule-based control model for multipurpose reservoir operation. Ponnambalam et al. (2003) combined a fuzzy inference system with artificial neural networks for operation of reservoirs. Mousavi et al. (2005) constructed a model called fuzzy-state stochastic dynamic programming (FSDP), which takes into account both uncertainties due to random nature of hydrological variables and imprecision due to variable discretization.

In real-time reservoir operation, it is important to forecast the stream-flow. In the last decade a new type of data-driven models, based on artificial intelligence and soft computing technique have been applied. In particular, Artificial Neural Networks (ANN) is one of the most widely used techniques in the forecasting field (e.g. Hsu et al. 1995; Shamseldin 1997; Thimuralaiah and Deo 2000). More recently, Fuzzy Logic (FL) (e.g. Hundecha et al. 2001and Chang et al. 2005) has also been used.

The purpose of this paper is to develop a fuzzy inference system model to forecast the stream-flow and then to control reservoir operation. A case study of the Zayandeh- Rood Reservoir is used to illustrate the approach.

2. Fuzzy inference system

Fuzzy set theory has been developed for modeling complex systems in uncertain and imprecise environment. A fuzzy set is an extension of a classical set whose elements may partially belong to that set. A fuzzy logic model is a logical-mathematical procedure based on an "If-Then" rule system that allows the reproduction of the human way of thinking in a computational manner. Generally, a fuzzy rule system has four components:

- Fuzzification of the input variables: the process that transforms the "crisp" input into a fuzzy input.
- Fuzzy rules: "If-Then" logic system as fuzzy rules links the input to the output variables.
- Fuzzy inference: the process that elaborates and combines the rule outputs.

- Defuzzification of the output: the process that transforms the fuzzy output into a crisp output.

The most popular methods for developing fuzzy rule systems are those proposed by Mamdani (1974) and Takagi et al. (1985). Thease methods are similar to the each other in many aspects. The first two parts of the fuzzy inference process -the fuzzification of the inputs and application of the fuzzy operator- are exactly the same in both methods. The main difference between methods of Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant. Generally, a fuzzy "If–Then" rule involves two parts. The first one is the "If" and the second one is the "Then" part which are called premise and consequence, respectively. The general form of a fuzzy "If–Then" rule is as follows:

Rule: If x is A then z is B

In the Mamdani method, *B* is a linguistic label; but in Sugeno's, *B* is either a linear or a constant statement. For example, a Sugeno FIS including two input variables x and y, one output variable f, and two fuzzy rules are as follows:

Rule 1: If x *is* A_1 *and* y *is* B_1 *then* $f_1 = p_1x+q_1y+r_1$
Rule 2: If x *is* A_2 *and* y *is* B_2 *then* $f_2 = p_2x+q_2y+r_2$

Where p_i, q_i, and r_i are the consequence parameters of ith rule and A_i and B_i are the linguistic labels which are represented by fuzzy sets. The degree of fulfillment of a pair (x, y) to rule i, which measures the degree to which that pair belongs to rule i, can be defined as

$$w_i = \mu_{A_i}(x) \otimes \mu_{B_i}(x) \quad (1)$$

Where $\mu_{A_i}(x)$ and $\mu_{B_i}(x)$ are membership functions of x and y in fuzzy sets A_i and B_i. '$\otimes$' denotes a fuzzy T-norm operator which is a function describing a set of fuzzy intersection (AND) operators, including minimum function or an algebraic product. In this study algebraic minimum was used as a T-norm operator. The final output of the system is the weighted average of all rules' outputs for the Sugeno method and centroid deffuzification for the Mamdani method.

$$\text{Final output} = \frac{\sum_{i=1}^{n} w_i f_i}{\sum_{i=1}^{n} w_i} \quad (2)$$

3. Case study

The Zayandeh-Rood basin as a closed basin lies in central Iran (Figure 1). The Zayandeh-Rood River is about 350 km long and runs in a roughly west-east direction, originating in the Zagros Mountains, west of the city of Isfahan, and terminating in the Gavkhuni Swamp to the east of the city. The Zayandeh-Rood River provides irrigation, domestic, and industrial water to Isfahan Province, which is one of the most important economic areas of Iran. The total area of the Zayandeh-Rood basin is about 41,500 km^2. However, only the area upstream of the Zayandeh-Rood reservoir makes significant contribution to the stream-flow. Below the reservoir there is actually no significant inflow to the river. The total water supply in the basin is augmented by the inter-basin transfer of water from the Kuhrang River in the upper Karoon river basin into the upper reaches of the Zayandeh-Rood River. Two diversion tunnels in operation since 1986 can deliver 540 million cubic meters of water per year while the third tunnel, has been operated recently, can deliver a further 250 million cubic meters of water annually.

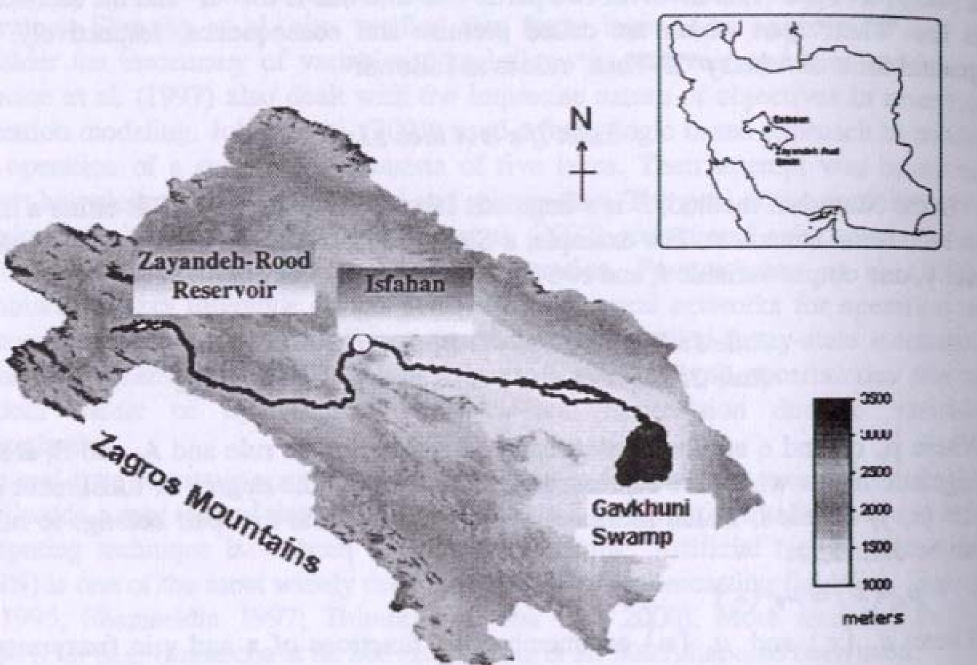

Figure 1: Location of Zayandeh-Rood basin, Iran

The Zayandeh-Rood River with an average annual flow of 992 million cubic meters (mcm), from a drainage basin of 4,200 km^2 enters Zayandeh-Rood reservoir. The reservoir capacity is over 1,460 mcm. This system supplies water for 120,000 ha of agricultural lands, major industries such as petrochemical and steel factories, and domestic use of the city of Isfahan and some other cities as well as interbasin water transfers to cities of Kashan and Yazd.

4. Model Construction

The system consists of two models. The first model forecasts seasonal stream-flow (SSF), then with use of the ratio of long-term average monthly to seasonal stream flow, monthly stream-flow (MSF) is predicted. With the predicted MSF, observed reservoir storage (S), year condition factor (YCF), and demand (D), the reservoir operating model makes the decision on the reservoir release in the current month.

The year condition factor determines hydrologic condition in each year. In other words, this factor divides each year into three classes; wet, normal, and dry. In this study, YCF is defined as:

$$YCF_n = \frac{I_{(n,2)}}{I_{max}} \tag{3}$$

Where, $I_{(n,2)}$ is the forecasted stream-flow (i.e. reservoir inflow) of season 2 in year n and I_{max} is the largest observed stream-flow of season 2 in the record.

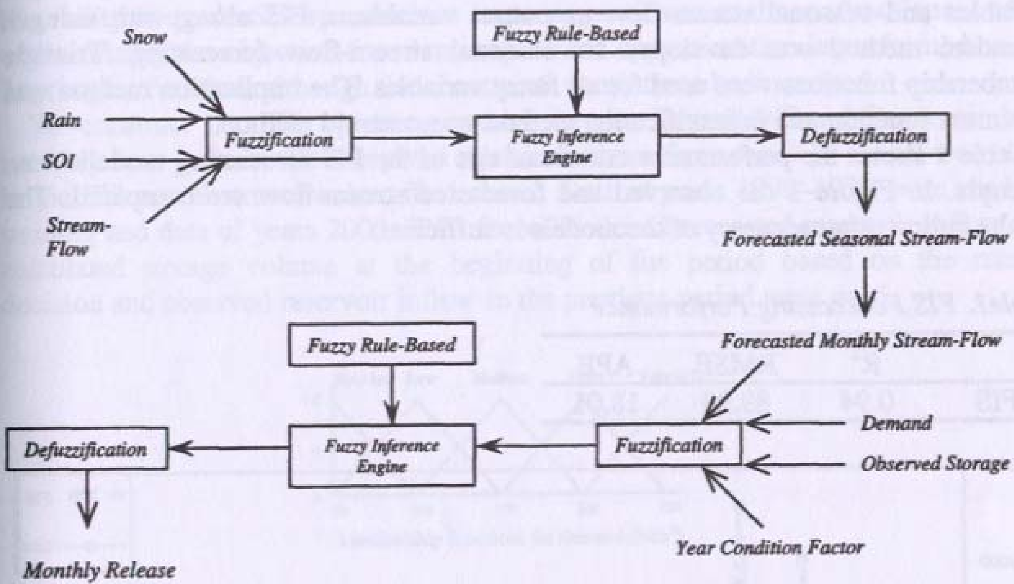

Figure 2: Structure of forecasting and operating models

4-1. Stream-Flow Forecasting Model

The purpose of seasonal forecasting model is to predict reservoir inflows. In order to have more accurate forecasts, each year is divided to three seasons; the snow accumulation season (December- February), the snow melt season (March-September), and the rest of the year. Furthermore, the Zayandeh-Rood basin is divided to three sub basins. For every season in each subbasin, a different forecasting model is constructed. In all models, the first step is determination of input variables. Previous studies shows that southern oscillation index, rain, snow, and stream-flow of previous periods are the most important explanatory variables for seasonal stream-flow forecasting in this basin (EWR Center, 2005).

Observed stream-flow data of the years 1990- 1999 were used for training and the years 2000- 2004 for validation. For comparison of forecasted and observed stream-flow, coefficient of determination ,R^2, root mean square, RMSE, and average percent error, APE, were used. They are defined as follows

$$R^2 = \left(\frac{\sum(Y_F - \bar{Y}_F)(Y_O - \bar{Y}_O)}{\sqrt{\sum(Y_F - \bar{Y}_F)^2 \sum(Y_O - \bar{Y}_O)^2}} \right)^2 \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum(Y_F - Y_O)^2} \quad (5)$$

$$APE = \sum\left[\frac{|Y_F - Y_O|}{Y_O} * 100\right] / n \quad (6)$$

Where Y_O is observed stream-flow, Y_F is forecasted stream-flow, $\bar{Y_O}$ is observed average, $\bar{Y_F}$ is forecasted average, and n is the number of observations.

Using the training data, including snow, rain, SOI, and stream-flow as input variables and seasonal stream-flow as output variable, a FIS along with using a Mamdani method was developed for seasonal stream-flow forecasting. Triangle membership functions were used for all fuzzy variables. The implication method was minimum function and defuzzification method was centroid method.

Table 1 shows the performance criteria of one of the FIS forecasting models as an example. In Figure 3 the observed and forecasted stream-flow are compared. The results indicate that accuracy of the models is sufficient.

Table1. FIS Forecasting Performance

	R^2	RMSE	APE
FIS	0.94	89.90	18.01

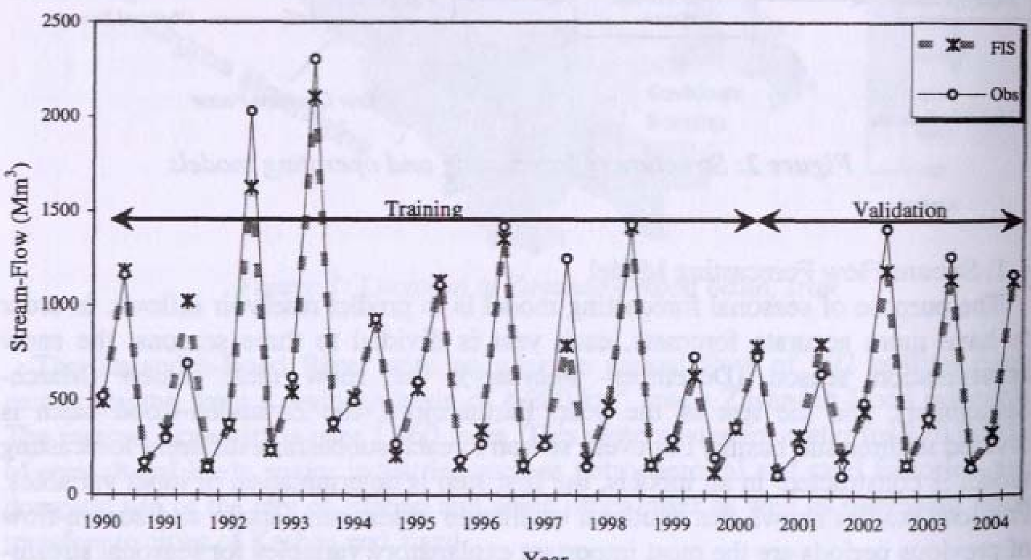

***Figure 3**: Comparison of forecasted and observed stream-flow*

4-2. Reservoir Operation Model

In modeling reservoir operation with a fuzzy inference system, the premises are: monthly forecasted stream-flow, reservoir storage, demand of each month, and year condition factor. The consequence is the release volume. In a fuzzy system, the rules are generally formed by using 'expert knowledge.' In the reservoir operation model of Panigrahi and Mujumdar (2000), for example, the fuzzy rules were derived from a long-term steady-state operation of the reservoir. For this purpose, a steady-state policy was derived using stochastic dynamic programming (SDP). In the present study, expert knowledge is derived using successive quadratic programming (SQP). The objective function used in the SQP is to minimize the expected value of the squared deviation of releases from the target demands. Reservoir storage and the inflow during a period form the two state variables in the SQP model. SQP relies on the computational efficiency of modern quadratic programming (QP) algorithms and the ability of quadratic expansions to better approximate nonlinear functions. Instead of linearizing the objective function, a quadratic approximation is performed on the Lagrangian function, although the constraints continue to be linearized.

To construct the FIS operating model for the Zayandeh-Rood Reservoir with monthly time periods, the computed release volumes from the SQP model were used in the FIS model structure described above. Data of years 1990–1999 were used for training and data of years 2000–2004 for validation. Forecasted reservoir inflow and calculated storage volume at the beginning of the period based on the release decision and observed reservoir inflow in the previous period were used.

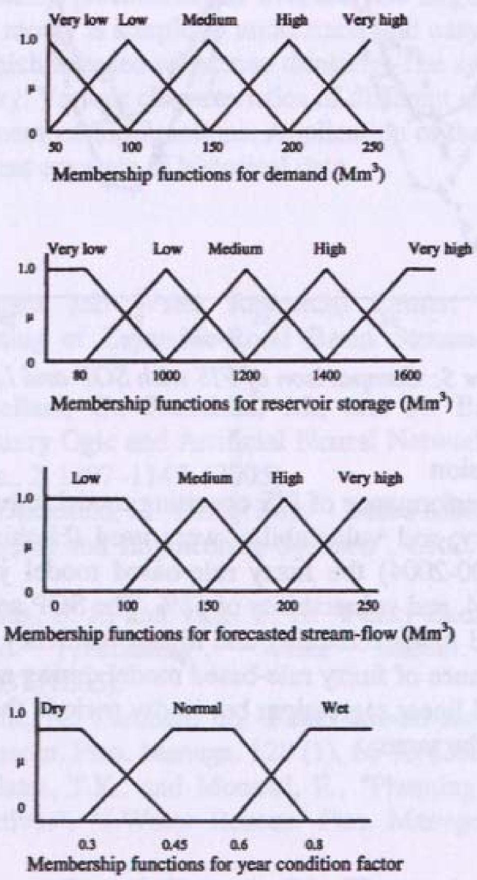

Figure 4: Membership functions of fuzzy variables

Membership functions were constructed for five levels of demand and storage, four levels of stream-flow and three levels of year condition factor (Fig. 4). The demand and storage were classified as: "very low," "low," "medium," "high," and "very high." Stream-flow was classified as "low," "medium," "high," and "very high."

The fuzzy operators of implication and aggregation together yield a fuzzy set for release. A defuzzifier (in this study, the centroid method) can convert this fuzzy set to a crisp release. In Fig.5 the results of fuzzy rule-based model and traditional reservoir operation methods such as SOP and linear regression (LR) are compared.

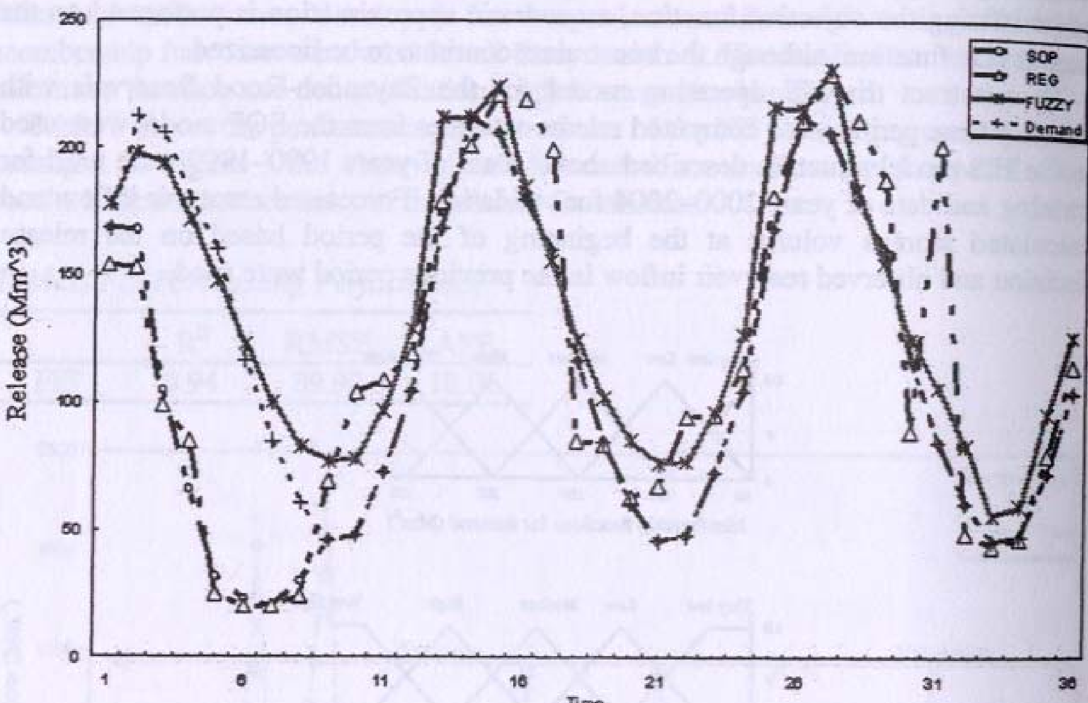

Figure 5: Comparison of FIS with SOP and LR

5. Results and Discussion

For evaluating the performance of FIS operating model, three performance criteria of reliability, resiliency, and vulnerability were used (Hashimoto et al., 1982). In validation period (2000-2004) the fuzzy rule-based model yielded a reliability of 82.6%, resiliency of 3.4, and vulnerability of 68%. The SOP and linear regression, on the other hand, yielded lower reliability and higher resiliency and vulnerability (see Table 2). The performance of fuzzy rule-based model during normal and wet periods is better than SOP and linear regression, but in dry periods the performances of FIS and SOP were almost the same.

Table2. Comparison of FIS, SOP and LR performance

Model	Vulnerability	Resiliency	Reliability
	Percent	*Months*	*Percent*
SOP	80	3.5	81
LR	84	4.5	69
FIS	65	3.4	83

6. Conclusions

Fuzzy rule-based models for forecasted seasonal stream-flow and for reservoir operation were developed in this paper. In the forecasting model, the Mamdani fuzzy inference model was used to forecast the seasonal stream-flow. In the operating model, a Sugeno fuzzy inference model controlled the reservoir monthly release. This study showed the good capability of the fuzzy rule-based models for stream-flow forecasting and reservoir operation.

An advantage of reservoir operation with a fuzzy inference system is that the complexity of optimization procedures are avoided and linguistic statement may be easily used. Thus, the model is simple to understand and easy to use by the operator due to its structure, which is based on human thinking. The system can also be easily adopted when necessary. Various characteristics of different reservoir systems can be encoded in rules and membership functions. Application of the model requires expert knowledge and sufficient amounts of historical data.

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