Real Time Operation Model for Optimum Operation of Bukan Reservoir in Lake Urmia Basin

Kayhan Gavahi[1], S. Jamshid Mousavi[2]

1- MSc. Student, School of Civil and Environmental Engineering, Amirkabir University of Technology

2- Professor, School of Civil and Environmental Engineering, Amirkabir University of Technology

Email: jmosavi@aut.ac.ir

Abstract

This paper presents an adaptive forecast-based mathematical model for real-time operation of Bukan reservoir located in Lake Urmia (LU) Basin. The model consists of three modules: 1) a forecasting module that predicts future inflows to the reservoir up to the end of a year, 2) a reservoir operation optimization module determining optimum reservoir releases and 3) an updating module that updates inflow forecasts and optimal releases at the beginning of every time step. As the forecasting module, an adaptive neural-based fuzzy inference system (ANFIS) is trained and used to forecast future inflows. Having these future inflows, a linear optimization model is formulated and solved to find optimal reservoir releases in future time steps of the year. The objective function of the model is to maximize total volume of water received by the lake while supplying water for irrigation demands and instream flow. The model is tested for 2015-2016 water year and its performance is assessed. Results obtained are promising in terms of volumes of water allocated to different demand sectors and preventing downstream areas from flooding caused by uncontrolled spillage. This is important as the system has experienced a severe flood in this particular year resulting in significant damages.

Keywords: Lake Urmia, Bukan Reservoir, Real Time Operation, Optimization.

1. INTRODUCTION

Climate change and human related activities has severely affected total inflow received by the Lake Urmia (LU) in the Northwest of Iran. Construction of various dams on the main rivers flowing to the lake and domestic and agricultural developments, which has resulted in increasing water demands in the past decade, has decreased the water level of the lake by 90% in September 2015. Climate change and increased irrigation demands are two main reasons for reduction in inflows to the reservoirs and much less water received by the lake. In this critical situation, the issue of improved operation of reservoiris to better meet the LU share from upstream reservoir releases has become more significant. Most of these reservoirs are multipurpose reservoirs functioning for water supply for downstream consumptive and non-consumptive demands and flood control. A number of contradictory objectives exist for operation of reservoirs of the basin. The first one is to store water as much as possible at the beginning of May to meet agricultural demands of future months up to about middle of September (end of water year) and the other one requires water releases in order to reserve reservoir capacity for the incoming flood. On the other hand, most of water releases made during irrigation season (May-September) will not reach the LU, resulting in critical adverse conditions in the lake. In other words, retaining water behind dams in winter months, to achieve higher reliability in meeting irrigation water demands, also causes significant reduction in the annual volume of water received by the LU that ultimately culminate in water level decline of the lake being drying up. Therefore, more careful and planned reservoir release schedule is needed accounting for the aforementioned conflicting objectives. In this line, a real-time reservoir operation modeling approach benefiting from forecasts of future inflows to reservoirs could be of help on how to best operate the basin's reservoirs [1]. The framework can provide insight on how to make best possible release decisions based on the most recent knowledge of future inflows. Having the most recent state of the system, forecasting models can determine the future state with a reasonable degree of uncertainty. Although the inherent forecast uncertainty will directly affect the results of this kind of operational models, improvements is expected to attain because of step-by-step reduction of forecast uncertainty as more information and data are received and the release decisions are updated [2], [3].

Two types of real-time reservoir operation models has been used in the literature [4]. Standard real-time operation models in which a streamflow forecasting model estimates future inflows only one time up to a specified short-run time horizon, and the decisions will be made based on these estimated predictions. This type of real-time operation models is mostly used for flood management purposes [5]–[8]. The second type is adaptive real-time operation models where the inflow-to-reservoir forecasts are updated step-by-step at the beginning of each time period of operation. It therefore has the chance to adapt itself to the most recent conditions and changes occurred in the system.

In this paper an adaptive real-time operation model is proposed for Bukan reservoir and its downstream system, which is the largest reservoir of the LU water basin built on the largest river of the basin, Zarinehrood, which provides nearly 40% of the total inflow to the lake. It is a multipurpose reservoir with the main objectives of water supply for agricultural, domestic and industrial uses, and controlling floods that occur mostly in spring season. Thus, a release schedule specifically accounting for the LU share is needed as a necessary requirement for the success of restoration plan of the lake. Therefore, the proposed modeling framework considers not only water supply to various demand sectors, it but also takes into account the LU water demand and share, especially in months prior to the crop season. The paper is organizing as follows: the proposed methodology is presented in section 2 with three subsections explaining inflow forecasting module, reservoir operation module and updating module, respectively. Section 3 introduces the case study and the data and information used followed by section 4 containing results obtained and discussing them. Finally, section 5 ends the paper by a summary and concluding remarks.

2. METHODS AND MODELING TOOLS

We explained that the real-time operation model consists of three modules. The forecasting module predicts the inflow to the reservoir up to a specified time horizon, *T*. Various types of forecasting methods including physics-based, time-series modeling and data-driven methods can be used in order to forecast future inflows to the reservoir. Having the future inflows, the reservoir operation module determines optimum releases in future months based on the water demands and various constraints of the system. Simulation, optimization or a combination of both could be used for this task. These two modules working together provide an efficient tool for making decision on how to operate the system in near future based on the most recent knowledge available. However, the longer the forecasting horizon of the prediction module, more uncertain future inflow forecasts will be. Therefore, the reliability of decisions made on future releases diminishes rapidly by heading toward the final time steps of the operation horizon (end of water year). This is where the last module plays an integral part by updating the model predictions at the beginning of each time step based on the most recent information received as the inputs for the forecasting module. The updating module also update the initial state of the system based on observed inflows and the latest changes in downstream demands and conditions.

Figure 1. illustrates how these three modules work together. We present the details of each module in the following subsections.

2.1. FORECASTING MODULE

An adaptive neural-based fuzzy inference system (ANFIS) model was developed and used as the forecasting module. ANFIS uses a combination of artificial neural network (ANN) and fuzzy logic approaches. It uses fuzzy inference system of Sugeno type to obtain final values of each decision variable [9], [10]. Using a hybrid learning mechanism that consists of the back-propagation gradient descent and a least squares methods, ANFIS determines the best possible set of parameters to map the given input-output set of data points. Thus model is a data-driven model that identifies the inherent function within a system without explicitly knowing the physical relationship between input and output variables.

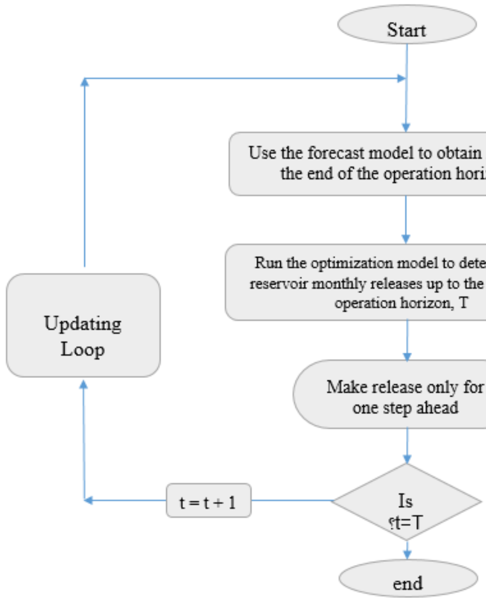

Figure 1. Flow diagram of the adaptive real-time reservoir operation model

Assuming a two dimensional input vector [x, y], the equivalent ANFIS structure that derives the output function *f* will be a five-layer feed-forward network shown in Figure 2. More detailed presentation of ANFIS for forecasting hydrological time-series can be found in the literature [11]–[15].

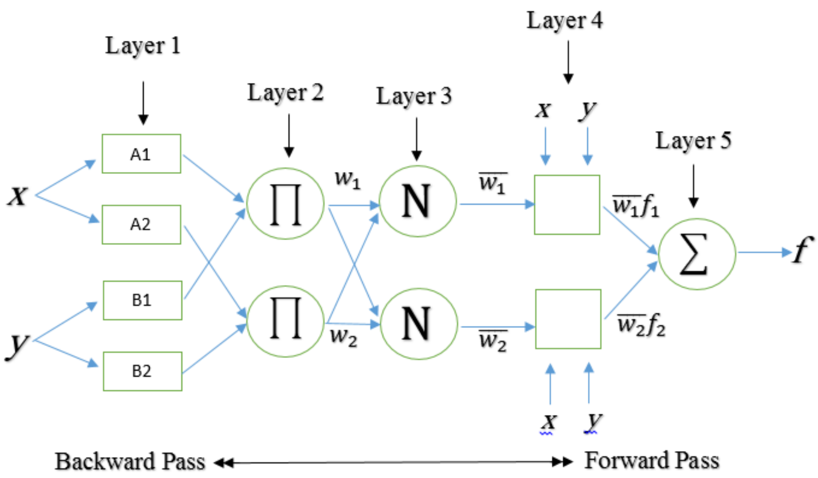

Figure 2. ANFIS structure for a two dimensional input vector [x, y] and output function *f*

2.2. Reservoir Operation Module

Figure 3. shows a schematic view of the Zarinerood River system including Bukan Dam. Based on the sum of water demands for each sector that are directly supplied by the Bukan reservoir, we have developed a linear mathematical model optimizing the system operations.

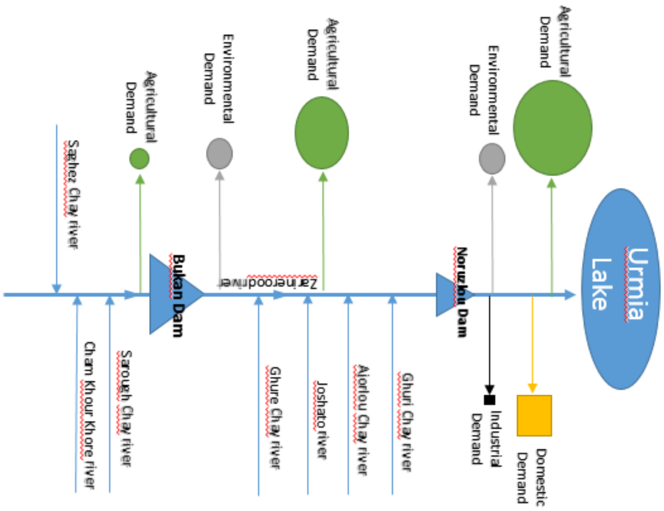

Figure 3. A schematic view of water inflows and withdrawals to the Zarinerood River downstream of Bukan Dam

The objective function of the proposed model is stated by equation 1. It is maximization of the benefits gained by releasing water for environmental instream flow, agricultural uses and the LU water demand. Each of these variables are accompanied by a priority coefficient. A larger coefficient for each user means a higher priority for water allocation to that user during shortages.

$$Max \qquad Z = \sum_{t=1}^{n} C_o R_{o_t} + C_a R_{a_t} + C_L R_{L_t} \tag{1}$$

In above equation n is the total number of time steps, C_o is the priority coefficient for environmental instream flow of Zarineroud River, C_a refers to priority coefficient for agricultural demands, and C_L is the priority coefficient for water received by the Lake Urmia. R_{o_t}, R_{a_t} and R_{L_t} are allocations for Zarineroud River, irrigation demands and the Lake Urmia, respectively. This objective function ensures that water is allocated first to minimum instream flow and minimum obligatory irrigation demands decreased by 40% compared to business-as- usual irrigation demands. After that the next priority is for the LU. Constraints of the mathematical program consist of water balance equations, upper bounds on water allocation values that must be less than the required demands and physical constraints regarding capacity of the reservoir and the downstream channels, especially at the inlet of Lake Urmia where fuse plugs are installed. They facilitate the release made for the lake reach the water body of the lake and prevent it from losing through seepage and evaporation in the buffer zone adjacent to the lake. Below is the set of constrains represented by equations 2 to 7:

$$S_1 \le S_n \tag{2}$$

$$S_{t+1} = S_t + Q_t - R_{a_t} - R_{d_t} - R_{i_t} - R_{o_t} - R_{L_t} - E_t - spil_t \tag{3}$$

$$R_{a_t} \le D_{a_t}, R_{d_t} = D_{d_t}, R_{i_t} = D_{i_t}, R_{o_t} \le D_{o_t} \tag{4}$$

$$R_{L_t} + R_{o_t} = Cap_{fuze} \tag{5}$$

$$S_{\min} \le S_t \le S_{\max} \tag{6}$$

$$\frac{R_{a_t}}{D_{a_t}} = \frac{R_{a_{t+1}}}{D_{a_{t+1}}} \tag{7}$$

where S_t and Q_t are the beginning-of-month reservoir storage and inflow to reservoir in month t, respectively. E_t and $spil_t$ are evaporation and spillage from the reservoir, respectively. D_{a_t}, D_{d_t}, D_{i_t} and D_{o_t} are agricultural, domestic, industrial and minimum instream flow requirements, respectively. $S_{\max}$ and $S_{\min}$ are respectively upper and lower bounds on the reservoir storage volume, and Cap_{fuze} is the capacity of the structures built at the inlet of the lake**.** Equation 7 ensures that if there exist any shortages and the annual irrigation demand cannot be fully met, shortages are distributed proportionately among irrigation months in an irrigation season [16]. Solution of this mathematical program contains optimum releases and allocation to different users.

2.3. UPDATING MODULE

According to figure 1, at the beginning of each time step, updating module will provide the ANFIS model with the most up-to-date observed data. These data include inflow to the reservoir, changes in downstream demands and also changes in downstream conditions that may result in changing the reservoir operation module coefficients. It also enables the ANFIS model to be trained once again in order to adapt itself and its parameters to observed inflows of previous time steps and therefore obtain higher performance in future inflow predictions. After forecasting future inflows of the next time steps up to the end of the operation horizon, T, the presented linear reservoir operation optimization model determines optimum releases and water allocations to different demands up to the end of the operation horizon. Since the forecasted inflows and therefore releases for more distant time steps are more uncertain and less reliable, only the reservoir release and water allocation for the immediate next time step ahead will be implemented. Having the observed inflow, the updating module simulates the system with actual values of inflow to the reservoir in order to determine the initial state of the system for the next time step.

Then if the model has not reached the final time step, the updating module collects the observed inflows and determines the initial state of the system, and forecasting and reservoir operation models are employed again. The procedure is repeated until reaching the end of operation time horizon that is the beginning of the next water year.

3. CASE STUDY

Lake Urmia (LU) water basin is located in northwest part of Iran. The basin takes its name from Urmia Lake located at the center of water basin. The lake suffers from dramatic decline in its water level and volume of water stored in it. In September 2015, the lake had only 10% of its potential storage capacity, a situation that seems to get worse if proper actions are not taken that could culminate in total loss of the lake. The largest river in the basin is Zarinehrood River. This river starts from Zagros mountain range and drains to Lake Urmia after flowing for about 350 km distance. It passes through three provinces of Kordestan, West and East Azarbaijan and contributes to about 41% of total surface water inflow to the lake. The drainage area of Zarinehrood River is about 12,000 km, and it crosses two cities of Shahindej and Miandoab [17]. Bukan reservoir as the largest reservoir in the basin has been constructed on this river for supplying water to agricultural, domestic and industrial water users. It has 810 million cubic meters (MCM) storage capacity and the long-term average annual inflow to the reservoir is about 1600 MCM. The outflows are distributed by the Norozlu diversion dam to about 85,000 hectares of Miandiab farming lands, and to three major cities such as Tabriz and its suburbs.

There are eight major dams being under operation in the basin discharging water to the lake and other demand points. The operation policies based on which the dams are operated directly affects the amount of water received by the lake throughout a year. Thus, it is important to use operation methods to account for downstream needs as well as considering the water required by the lake in order to survive. It should be noted that temporal variation of water released for LU is as important as the total quantity of water received. Releasing high amount of water in a shorter period of time not only can cause damages in downstream urban and agricultural areas, it but also results in damaging a number of structures and fuse gates built to facilitate transferring water to the main water body of the lake and prevent it from losing by evaporation.

4. RESULTS AND DISCUSSION

The proposed adaptive real-time model is tested for planning the operation of Bukan reservoir for a typical year. The operation horizon was considered to be one year with monthly time steps. However, the model has the ability to be used for any desired time horizon and time steps as long as the two first modules are adopted with the desired reliability. Using the 34 years available historical inflow time series, we trained and validated an ANFIS-based inflow forecasting model. Three previous monthly inflows were used as input to the model to forecast the future inflows to the reservoir. For example, if we are at the beginning of September, the ANFIS model uses inflows in June, July and August and predicts inflows to the reservoir during September. Having estimated inflows to the reservoir in September, August and July as inputs to the ANFIS model, the model will forecast October's inflow and so on. This procedure is continued up to the last month of the planning horizon until inflow values of all future months are predicted. Note that the predicted inflow for September has a certain amount of error and uncertainty. This error will propagate through inflow forecast of all future months, therefore, forecast errors are accumulated as we go ahead. In this regard, the updating module helps us significantly reduce the forecast error and adapt the model to inflow changes by involving actual observed values into the model at the beginning of each time step.

Table 1. reports water demands for various users to be supplied exclusively by Bukan reservoir. Agricultural demands are about 58% of total water demand. Noting that the storage capacity of the reservoir is 810 Million Cubic Meters (MCM), volume of withdrawal for irrigation purposes is relatively considerable. Also 95% of annual irrigation demand belongs to the main crop season, i.e. May to September. Interestingly, only less than 15% of total annual inflow occurs in this period; therefore, the role of the reservoir storage to regulate natural inflows would be essential. Because of high water demands and farmers tendencies to use water in the crop season, releases made to reach LU (R_{L_t}) are more likely to reach the lake during time periods other than the crop season.

Table 1- Demands for various sectors downstream of Bukan Dam (all values are in MCM).

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sep	sum
Agriculture Demand (Da)	1.9	18.3	0	0	0	0	0	51.2	90.9	81.6	99.5	72.8	**416.2**
Domestic Demand (Dd)	11.5	10.2	9.8	9.8	10.3	10.5	10.5	14.1	12.5	13.5	14	15.1	**141.7**
Industrial Demand (Di)	0.5	0.5	0.5	0.5	0.5	0.5	0	0	0	0	0	0	**3**
Environmental Demand (Do)	18.1	10	9	5	13.5	13.5	20	13.5	13.5	13.5	13.5	13.5	**156.6**

According to high priority of meeting domestic and industrial water demands, the reservoir releases for this type of demands are incorporated as rigid constraints of the reservoir operation module in the model (equation 4), so they must be met regardless of yearly variations of inflow to the reservoir.

The proposed model is tested for year 2015-2016 with monthly inflows shown in figure 4. It can be seen that inflow to reservoir in April is 517 MCM, which is 64% of total capacity of Bukan reservoir. This huge amount of input resulted in uncontrolled spillage and heavy damages downstream. The problem was mostly because of not having a suitable tool to forecast this event in advance and operate the reservoir smartly in such a critical situation. In this case, inflows in months prior to the crop season was stored and was not released on time to provide with enough storing capacity for incoming floods in Spring. It is of interest to test the proposed real time model and see if it can improve the situation in a real life operation context.

Table 2. presents the results obtained by the adaptive real-time operation model proposed. We can see that water demands for agricultural, domestic, industrial and environmental are completely met. Also the sum of spilled water is zero showing that it has successfully prevented unwanted spillage by releasing water for LU in January, February and March with the amounts of 156.4, 171.5 and 171.5 MCM, respectively. Therefore, the resulting end of month (EoM) storage of March is determined to be 422.5 MCM, which is nearly half of the capacity of Bukan reservoir. This allowed having enough space left for the incoming 517 MCM inflow in April and managing the flood occurred in this year with a volume of 300 MCM. This has been made possible mainly by the updating capacity of the proposed framework.

Table 2- Demands for various sectors downstream of Bukan Dam (all values are in MCM).

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	June	Jul	Aug	Sep	sum
EoM storage	245.2	279.4	345.1	302	329	422.5	740.7	785.7	671.8	551.9	417.8	308.3	
Agricultural Release	1.9	18.3	0	0	0	0	0	51.2	90.9	81.6	99.5	72.8	**416.2**
Domestic Release	11.5	10.2	9.8	9.8	10.3	10.5	10.5	14.1	12.5	13.5	14	15.1	**141.7**
Industrial Release	0.5	0.5	0.5	0.5	0.5	0.5	0	0	0	0	0	0	**3**
Environmental Release	18.1	10	9	5	13.5	13.5	20	13.5	13.5	13.5	13.5	13.5	**156.6**
LU Release	0	0	0	**156.4**	**171.5**	**171.5**	**165**	**76.2**	**15.7**	0	0	0	**756.2**
Spillage	0	0	0	0	0	0	0	0	0	0	0	0	**0**
Env+LU Release	18.1	10	9	161.4	185	185	185	89.7	29.2	13.5	13.5	13.5	**912.8**

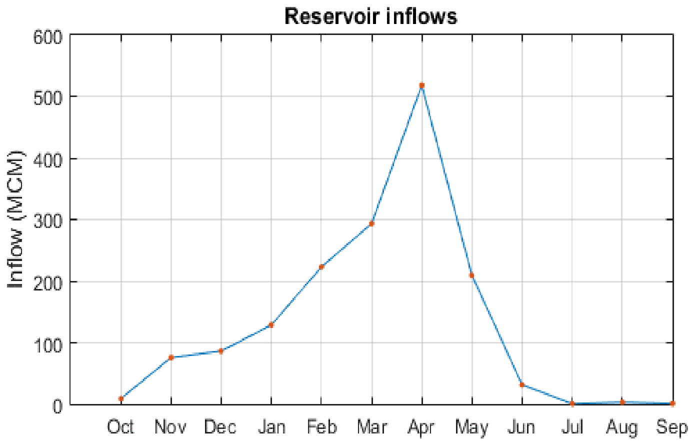

Figure 4. Monthly inflows to Bukan reservoir for the tested water year (2015-2016).

5. CONCLUSIONS

This paper presented an adaptive real-time operation framework proposed for forecast-based optimal operation of Bukan reservoir in Lake Urmia. It consists of a streamflow forecast module, a medium-term reservoir operation optimization module and an updating procedure to adjust the forecasted inflows and the reservoir releases as time moves forward and the planning horizon becomes shorter. Testing the proposed methodology, an adaptive network-based fuzzy inference system (ANFIS) developed for inflow forecasting coupled with a linear operation optimization model performed well enough for the Bukan system operation in year 2015-2016 in terms of supplying water for agricultural, domestic, industrial and environmental uses as well as controlling a severe flood experienced in this year. It provided LU with 756.2 MCM of water released in months prior to the crop season, which is the desired time period to make releases for LU.

6. REFERENCES

1. Nohara, D., & Hori, T. (2017). Integrated Reservoir Operation Considering Real-Time Hydrological Prediction for Adaptive Water Resources Management. In Sustainable Water Resources Planning and Management Under Climate Change (pp. 101-132). Springer Singapore.
2. Chen, L., Singh, V. P., Lu, W., Zhang, J., Zhou, J., & Guo, S. (2016). Streamflow forecast uncertainty evolution and its effect on real-time reservoir operation. Journal of Hydrology, 540, 712-726.
3. Nohara, D., Nishioka, Y., Hori, T., & Sato, Y. (2016). Real-Time Reservoir Operation for Flood Management Considering Ensemble Streamflow Prediction and Its Uncertainty. In Advances in Hydroinformatics (pp. 333-347). Springer Singapore.
4. Mujumdar, P. P., & Ramesh, T. S. V. (1997). Real-time reservoir operation for irrigation. Water Resources Research, 33(5), 1157-1164.
5. Unver, O. I., & Mays, L. W. (1990). Model for real-time optimal flood control operation of a reservoir system. Water resources management, 4(1), 21-46.
6. Wasimi, S. A., & Kitanidis, P. K. (1983). Real-time forecasting and daily operation of a multireservoir system during floods by linear quadratic Gaussian control. Water Resources Research, 19(6), 1511-1522.
7. Hsu, N. S., & Wei, C. C. (2007). A multipurpose reservoir real-time operation model for flood control during typhoon invasion. Journal of Hydrology, 336(3), 282-293.
8. Huang, W. C., & Hsieh, C. L. (2010). Real-time reservoir flood operation during typhoon attacks. Water Resources Research, 46(7).
9. Jang, J. S. (1993). ANFIS: adaptive-network-based fuzzy inference system. IEEE transactions on systems, man, and cybernetics, 23(3), 665-685.
10. Jang, J. S. R., Sun, C. T., & Mizutani, E. (1997). Neuro-fuzzy and soft computing: a computational approach to learning and machine intelligence.
11. Firat, M., Turan, M. E., & Yurdusev, M. A. (2009). Comparative analysis of fuzzy inference systems for water consumption time series prediction. Journal of hydrology, 374(3), 235-241.
12. Firat, M., & Güngör, M. (2008). Hydrological time-series modelling using an adaptive neuro-fuzzy inference system. Hydrological Processes, 22(13), 2122-2132.
13. Keskin, M. E., Taylan, D., & Terzi, O. (2006). Adaptive neural-based fuzzy inference system (ANFIS) approach for modelling hydrological time series. Hydrological sciences journal, 51(4), 588-598.
14. Zounemat-Kermani, M., & Teshnehlab, M. (2008). Using adaptive neuro-fuzzy inference system for hydrological time series prediction. Applied Soft Computing, 8(2), 928-936.
15. Nayak, P. C., Sudheer, K. P., Rangan, D. M., & Ramasastri, K. S. (2004). A neuro-fuzzy computing technique for modeling hydrological time series. Journal of Hydrology, 291(1), 52-66.
16. Ilich, N. (2011). Improving real-time reservoir operation based on combining demand hedging and simple storage management rules. Journal of hydroinformatics, 13(3), 533-544.
17. Yasi, M., & Ashori, M. (2017). Environmental Flow Contributions from In-Basin Rivers and Dams for Saving Urmia Lake. Iranian Journal of Science and Technology, Transactions of Civil Engineering, 41(1), 55-64.