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Comparison of Two Data-Driven Streamflow Forecast Approaches in an Adaptive Optimal Reservoir Operation Model

Kayhan Gavahi[1], S. Jamshid Mousavi[2*] and Kumaraswamy Ponnambalam[3]
[1] MSc. Student, School of Civil and Environmental Engineering, Amirkabir University of Technology, Tehran, Iran
[2] Professor, School of Civil and Environmental Engineering, Amirkabir University of Technology, Tehran, Iran
[3] Professor, Systems Design Engineering, University of Waterloo, Waterloo, Canada
kayhangavahi@gmail.com, jmosavi@aut.ac.ir, ponnu@uwaterloo.ca

Abstract

This study investigates the effect of two data-driven inflow prediction methods on the performance of a proposed adaptive real-time optimum reservoir operation model. The model consists of three modules; a forecasting module, which predicts the monthly future inflows, a reservoir operation optimization module, determining monthly optimum reservoir releases up to the end of a year, and an updating module, updating the current state of the system and provides the other two modules with the latest observed information on future inflows. K-nearest neighbor (KNN) and adaptive neuro-fuzzy inference system (ANFIS) approaches are used to forecast monthly inflows to the reservoir. The results demonstrate that ANFIS outperforms the KNN approach by 25, 23, 27 and 10 percent with respect to RMSE, PWRMSE, NSCE and correlation coefficient indices, respectively. However, the objective function values of the reservoir operation optimization model associated with each of those forecast models reveal that ANFIS-based adaptive reservoir operation model is only 5% better than the KNN-based model. This observation highlights the significance role of adaptation and updating procedure in the reduction of streamflow forecast errors.

Keywords: Adaptive Reservoir Operation, Inflow Forecasting, KNN, ANFIS.

* Corresponding Author

1 Introduction

Efficient operation of surface water reservoir systems is of the first rate of importance for most of the developing countries, especially when water scarcity continues to be a major problem (Vedula & Mohan, 1990). This problem continues to be a challenge due to complexity and uncertainty issues involved in these systems (Russell & Campbell, 1996). Uncertainties are mostly in water demands, future condition of the system and inflows to the reservoir. Real-time operation approach has proven to be a powerful tool for tackling uncertainties since it uses the most recent information available in order to make decisions for near future (Akbari-Alashti, Bozorg Haddad, Fallah-Mehdipour, & Mariño, 2014; Bolouri-Yazdeli, Bozorg Haddad, Fallah-Mehdipour, & Mariño, 2014; Che & Mays, 2015). Two types of real-time operation models have been proposed in the literature (Mujumdar & Ramesh, 1997). Standard real-time operation models in which streamflow forecasting will be conducted once to estimate future inflows up to a relatively short-time horizon, and decisions will be made based on the inflow forecasts for the near future. This type has been mostly used for flood management purposes (Che & Mays, 2017; Hsu & Wei, 2007; Huang & Hsieh, 2010; Unver & Mays, 1990; Wasimi & Kitanidis, 1983). The second type, on the other hand, is adaptive real-time operation models where the inflow forecasts and the decisions made upon those forecasts are updated step-by-step at the beginning of each time period. Therefore, adaptive real-time operation models have the ability to update the decisions in predefined time periods to adapt to the changes occurred within the operation horizon. This adaptation process helps correct the previous mistakes regarding inflow predictions and lower the effects of uncertainty involved in streamflow forecasting. Dagli et al. (1980) described an adaptive real-time operation method, called as adaptive planning, to determine operating policies for a set of four reservoirs. In his method a forecast was made at the beginning of each time step for future inflows, and then using the forecasted values a deterministic model of the system was solved in order to obtain releases for the next time step. The forecast values were updated and the model was ran again at each successive time step to the end of the operation time horizon. He showed that the model results were within the 0.4% of the optimal solution for a period of 5-year operation (Dagli & Miles, 1980). Zhao et al. (2014) considered the effects of uncertainties of long- and short-term streamflow forecasts on the reservoir operation decision-making processes. They used a sliding carried-over storage strategy to circumvent the terminal storage effect. The results showed that using the same forecasting method, their strategy reduced the uncertainties in the process of release decisions (Zhao & Zhao, 2014). This study focuses on the impact assessment of two different inflow forecast methods with different levels of accuracy on an adaptive forecast-based optimum reservoir operation model. The main goal is to quantitatively show that adaptation and updating processes could reduce the negative effects of forecast errors. Consequently, an adaptive reservoir operation model is proposed, consisting of three modules. The modules include an inflow forecast module, a yearly reservoir operation optimization module with a monthly time step and an updating module. Two inflow forecast methods of KNN and ANFIS are tested to assess how the overall performance of the proposed model is affected by the uncertainties in inflow forecasts. The model was tested on Bukan reservoir, the largest reservoir in Lake Urmia (LU) water basin in northwest of Iran. The reservoir has been built on Zarinehrood river which has the highest contribution to supplying water to LU. Climate change, construction of eight large dams, agricultural developments and population growth has dramatically reduced the amount of annual inflow to the LU, resulting in severe water level decline. Therefore, better reservoir operation considering water releases for LU as one of the main priorities is necessary for LU restoration. In the next section, the proposed methodology is briefly explained. Afterwards, the model results are presented and discussed followed by a conclusion section.

2 Methodology

In this section, first, the proposed adaptive real-time operation model will be briefly explained. Then the streamflow prediction methods, employed in the forecasting module of the model are presented.

2.1 Adaptive Reservoir Operation Model

An adaptive reservoir operation model is proposed in this study. The model consists of three modules: 1) a forecasting module by which future monthly inflows to the reservoir from the current time step to the end of the operation horizon are estimated, 2) an optimization module determining the optimum releases from the reservoir for the current time step to the end of the operation horizon and 3) an updating module transferring the initial state of the system to the next time period and provides the other two modules with the most recent observed inflows. Figure 1 shows the flowchart of the proposed model. The reservoir operation optimization module is a linear program-based model.

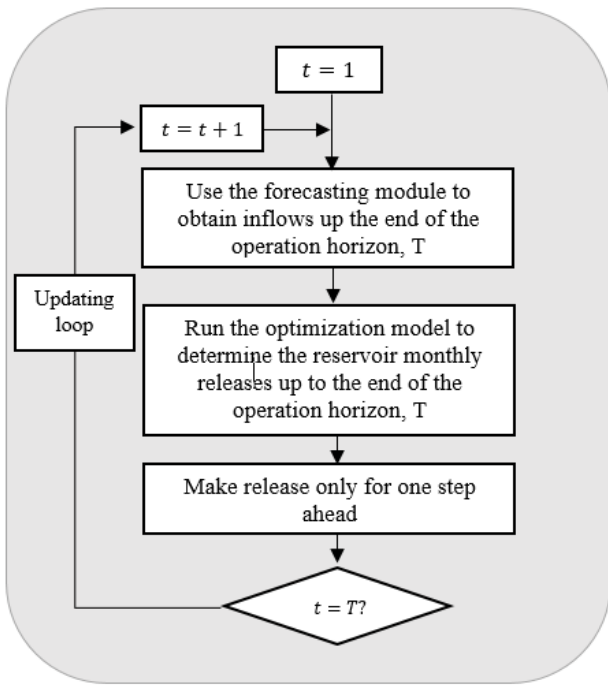

Figure 1: Flowchart of the proposed real-time model

Equation 1 shows the objective function of the mathematical model proposed for Bukan reservoir-streamflow water system. The function is the maximization of total water released for three major sectors, including environmental instream flow allocated for Zarinehrood river, agricultural sector and water released specifically for LU. A priority coefficient is associated with each of these purposes. A larger coefficient for each user implies 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 this equatio 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 LU. R_{o_t} , R_{a_t} and R_{L_t} are allocations for Zarineroud River, irrigation demands and LU, respectively. This objective function ensures that water is allocated first to minimum instream flow and minimum obligatory 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 the capacity of the reservoir and downstream channels, especially at the inlet of Lake Urmia where fuse plugs are installed. They facilitate the release made for the lake to 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 constraints 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 end-of-month reservoir storage and inflow to the 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 (Ilich, 2011). The solution of this mathematical program provides optimum releases and allocations to different users.

2.2 Inflow Forecast Method

As it was mentioned in the previous section, the first module of the proposed model is an inflow forecast model by which future monthly inflows to the reservoir. There are a variety of methods used for streamflow prediction in the literature (Chang & Chen, 2001; Valipour, Banihabib, & Behbahani, 2013; Faber & Stedinger, 2001; El-Shafie, Taha, & Noureldin, 2007; Jain, Das, & Srivastava, 1999). In this study two data-driven methods, i.e. K-nearest neighbour (KNN) and adaptive neuro-fuzzy inference system (ANFIS) are used separately as the forecasting module of the reservoir operation model. KNN works based on similar situations occurred in the past with the current state of the system, and ANFIS translates the relationships between subsequent inflows as fuzzy if-then rules parameters of which are fine-tuned by a neural network structure. Both of the methods are trained to forecast the one-month ahead inflow to the reservoir conditioned on three previous observed streamflow values.

2.3 Updating Procedure

According to figure 1, the most recent observed data will be supplied to the forecasting module at the beginning of each time step. Having these data, the forecasting module updates future inflow forecasts to the reservoir, considering the observed inflows in the previous time steps. At the same time, the forecast model is trained again to adapt its parameters to the observed inflows. Having determined future inflow forecasts, the reservoir operation module determines optimum reservoir releases and allocations for various demands up to the end of the operation horizon, *T*. Since the inflow forecasts and releases for more distant time steps are more uncertain and less reliable, only the reservoir release and allocations for the immediate next time step ahead will be implemented. Afterward and at the end of the current time step, the updating module simulates the system once more to determine the actual initial state of the system, ready to be used for the next time step. Additionally, the algorithm checks if the last time step has been reached or not. The procedure will continue until it reaches the end of operation time horizon that is the beginning of the next water year.

3 Results and Discussions

The proposed model is applied and tested in Bukan Dam reservoir system in Lake Urmia Basin in Iran. The basin gets its name from Lake Urmia suffering from severe input water decline that is drying up. Bukan is the largest reservoir in the basin constructed on the Zarinehrood River. The river contributes to 41% of total inflow to the lake; therefore, optimum operation of Bukan reservoir, considering the objective of releasing water for the lake, is at paramount importance to the three states surrounding this lake (Yasi & Ashori, 2016). Thirty four years of inflow data to Bukan reservoir is available of which the first 26 years are used for the training set and the last 8 years for validation. Figure 2 shows observed inflows versus predicted values using the two proposed data-driven methods for the mentioned 8-year period. As for the ANFIS method, the points are more narrowed around the $y=x$ line, which shows a better correlation of its outputs with respect to the observed inflows. Also, the R-square value is 17 percent better than that of KNN method. In Figure b points are more scattered, which is indicating lower prediction performance, especially for inflows between 200 to 500 MCM. Table 1 also shows the performance of the forecast methods employed with respect to the validation data set. Four performance indices, i.e. root mean square error (RMSE), peak weighted root mean square error (PWRMSE), Nash-Sutcliff error (NSCE) and correlation coefficient are considered to compare the performance of the two methods.

Results presented in Table 1 show that ANFIS outperforms the KNN method in terms of all four indices defined. The RMSE and PWRMSE measures obtained for the ANFIS method are 25% and 23% is lower than those of KNN, respectively. Also the NSCE and correlation coefficient for this method are respectively 0.27 and 0.10 higher than those of KNN. Subsequently, each of these two methods is employed in the proposed adaptive reservoir operation model using the validation set time series data. The main goal here is to evaluate the impact of using either KNN or ANFIS method on the objective function value of the operation model. The resulted objective function for the two inflow forecast methods is then compared with the objective function value of an ideal model having perfect foresight on future inflows. In the perfect model, it is assumed that all future monthly inflows are known. This is an ideal case representing an optimum operation situation, in case there would be no forecast errors in inflow forecasts. Consequently, it finds the best possible solution that can potentially be achieved. Table 2 shows the objective function values using these three scenarios.

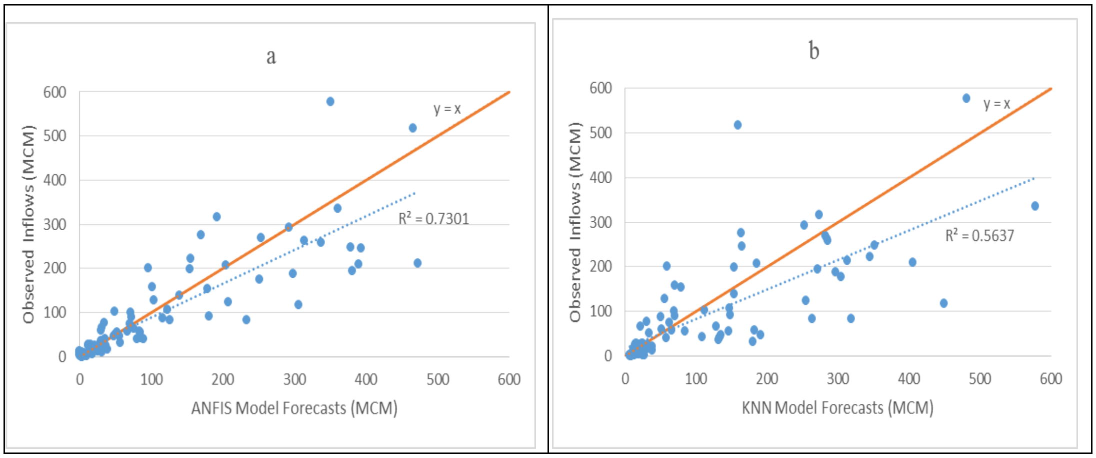

Figure 2: a) ANFIS model forecasts versus observed inflows. b) KNN model forecasts versus observed inflows

Performance index	KNN	ANFIS
RMSE (MCM)	87.7	65.7
PWRMSE (MCM)	114.6	88.6
NSCE	0.38	0.65
R	0.75	0.85

Table 1: Performance indices of two forecast methods

Results presented in Table 1 show that ANFIS outperforms the KNN method in terms of all four indices defined. The RMSE and PWRMSE measures obtained for the ANFIS method are 25% and 23% is lower than those of KNN, respectively. Also the NSCE and correlation coefficient for this method are respectively 0.27 and 0.10 higher than those of KNN. Subsequently, each of these two methods is employed in the proposed adaptive reservoir operation model using the validation set time series data. The main goal here is to evaluate the impact of using either KNN or ANFIS method on the objective function value of the operation model. The resulted objective function for the two inflow forecast methods is then compared with the objective function value of an ideal model having perfect foresight on future inflows. In the perfect model, it is assumed that all future monthly inflows are known. This is an ideal case representing an optimum operation situation, in case there would be no forecast errors in inflow forecasts. Consequently, it finds the best possible solution that can potentially be achieved. Table 2 shows the objective function values using these three scenarios.

	Adaptive operation model using KNN-based forecasts	Adaptive operation model using ANFIS-based forecasts	Perfect Model
Objective function value (MCM)	$3.4383e10^4$	$3.6444e10^4$	$4.0484e10^4$

Table 2: Objective function values of three models

The results indicate that the model objective function values for the models benefiting from KNN and ANFIS forecast modules have reached 85 and 90 percent of the best objective function associated with the perfect model, respectively. One important point is that although the ANFIS method outperformed the KNN method by 25 and 23 percent in terms of RMSE and PWRMSE performance indices, their difference with respect to the reservoir operation performance measure (objective function value) is only about 5 percent. This reveals how efficient the updating and the adaptation mechanism employed in the model is. Note that in the proposed adaptive operation model, among all the optimal releases obtained by the optimization module for all future time steps, only the release for the next time period is applied, after which the forecast values and future releases are updated by re-execution of both forecast and reservoir operation modules.

As it was mentioned in previous sections, the objective function consists of three variables. Two of these variables are, water released for agricultural demand and water released for LU. The variation of these two variables during an 8-year testing period has been plotted in Figures 3 and 4. The historical data of water demand for agricultural sector showed that each year had different crop pattern and crop area. These differences resulted in different yearly water demand, in which 2011-12 was the year with lowest (348.2 MCM), and year 2009-10 with 580.3 MCM was the year with highest agricultural demand. Since the perfect model is completely aware of all the monthly future inflows, it provides us with the upper bound for water releases made for agricultural sector, so the is no water shortage occurred and agricultural demand has been fully met for all years. The adaptive operation model using ANFIS and KNN as inflow forecasting methods has been able to meet 98% and 92% of the demand for this sector, respectively. It shows that the adaptive operation has been successful in terms of meeting downstream demands. Changing from ANFIS, which outperformed KNN by nearly 25%, resulted in only 6% difference in meeting agricultural demands. This means the proposed updating procedure incorporated in the adaptive operation model has significantly reduced the effects of inflow forecast errors. It is seen in Figure 3 that the performances of the proposed three models are almost identical, especially for the first 5 years. Considering water releases for LU, KNN-based adaptive operation model released a total amount of 1850 MCM, whereas the ANFIS-based adaptive model and the perfect model released 1695 MCM and 2023 MCM, respectively. Again, there is only 7% difference between ANFIS-based and KNN-based models. This proves the significant role of adaptation procedure in mitigating inflow forecast errors and optimal releases and allocations. Figure 4 shows how close are the performances of the three models considering water releases made for LU.

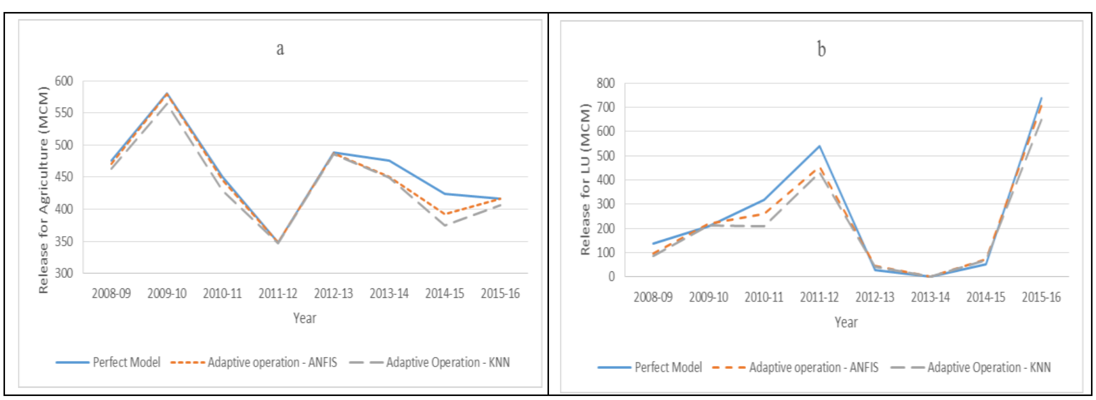

Figure 3: a) Water releases made for agricultural demand during the 8-year testing period for the three proposed models. b) Water releases made for LU during the 8-year testing period for the three proposed models

4 Conclusion

We assessed in this study the role of employing two different forecast methods of inflow to the reservoir on the overall performance of an adaptive forecast-based reservoir operation optimization model. The proposed model was used and tested in Bukan Dam river-reservoir system in Lake Urmia Basin. The KNN and ANFIS methods were trained and tested as the inflow forecast module of the model. The results demonstrate that ANFIS is better than KNN with respect to forecast accuracy measures as it outperforms the KNN method by 25, 23, 27 and 10 percent in terms of RMSE, PWRMSE, NSCE and correlation coefficient performance indices, respectively. However, the objective function value of the ANFIS-based adaptive operation model is only 5% better than that of the KNN-based model. This shows how efficient the adaptation and updating procedure used in the proposed model performs in coping with the forecast error and uncertainty.

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