Adaptive forecast-based real-time optimal reservoir operations: application to Lake Urmia

Keyhan Gavahi, S. Jamshid Mousavi and Kumaraswamy Ponnambalam

ABSTRACT

Boukan Dam reservoir is the largest infrastructure constructed on the Zarineh-Roud River regulating streamflow for different uses including supplying water to Lake Urmia, the second largest salt lake in the world. This paper presents a forecast-based adaptive real-time optimal operation model (ARTOM) for Boukan reservoir with the aim of maximizing releases feeding the lake while meeting other needs such as irrigation, industrial, and domestic uses. Adaptive neuro-fuzzy system-based inflow-to-reservoir forecasts are used in the ARTOM to determine optimal releases from the reservoir for future months up to the end of a year, but only the current period's release is applied. At the beginning of the next period, the forecasts are updated, and the procedure is repeated until the last period of the year. Additionally, the optimal terminal end-of-year reservoir storage volume is a dynamic updating input to the ARTOM, which is estimated from the results of a long-term reservoir operation optimization model. The ARTOM performance is tested against the last nine-year monthly data not utilized for training the forecast module. Results demonstrate that the ARTOM attains an objective function value very close to the best possible value that can ever be reached by utilizing an ideal operation model, benefiting from perfect foresight on future streamflows.

Key words | adaptive optimization, Lake Urmia, real-time reservoir operation, streamflow forecasting

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INTRODUCTION

Climate change and human-induced activities have severely affected total inflow received by Lake Urmia (LU) in the northwest of Iran, the second largest salt lake in the world. Additionally, construction of several dams on the main rivers flowing into the lake and domestic and agricultural developments, resulting in significant increased water demands in the past decade, have all caused the water level of the lake to decrease by 90% in September 2015 compared to that in 2000 (Yasi & Ashori 2016). Although climatic issues and reduction in precipitation in the past decade have been important in lowering inflows to the lake, irrigation-dominated reservoir release policies neglecting the water rights of natural ecosystems and LU have been more influential on the decline of the LU water level. Due to critical conditions of the LU drying out that will endanger the life of millions of people living in three provinces around the lake, i.e., Kordestan, Western Azarbaijan and Northern Azarbaijan, and its negative impacts on the ecosystem and economy of the region, the government of Iran formed a newly established organization in 2013 to prepare an action plan, i.e., Urmia Lake Restoration Program (ULRP), to help reverse this critical situation. The ULRP is responsible for managing and coordinating all activities to reverse the current situation and restore the lake ecosystem. One of the first main activities of the ULRP that all responsible parties agreed upon was to decrease the total irrigation demand by 40% during a five-year period from 2014 to 2019. This is important in increasing the total annual flow received by the LU to about 1.7 billion cubic meters and bringing the lake's water level to an ecologically minimum required level. Under such conditions, it would be crucial to operate dams in a way that

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they release water to the lake in both a timely and adequate way. Most of the reservoirs in the basin are multipurpose, functioning for the conflicting objectives of water supply for consumptive and non-consumptive uses and flood control. On the one hand, the ministry of energy (MoE) people, responsible for dam operations, try to fill the reservoirs before the middle of April to have enough water for use in irrigation during April to September. On the other hand, they are concerned about possible large incoming floods that historically occur in March and April. Besides these objectives, the MoE is now more responsible than before to release water for the LU itself as much as possible, while there is no guarantee that the water released to feed the LU in the irrigation season is not withdrawn by farmers in dry years.

All the above-explained situation has made the planning of dam reservoir operations much more important and complicated than before, with more parties and stakeholders playing a role in the game. The main stakeholders are ULRP as the coordinating body, MoE responsible for making releases from the reservoirs, Ministry of Agriculture Jihad (MoAJ) representing the main consumer of water in the basin, and National Environmental Organization, responsible for LU ecosystem protection and minimum instream flows. Therefore, the water resources task force of the ULRP has made an attempt to propose operational models to derive appropriate reservoir operation rules and policies reflecting the mentioned complex, conflicting needs and expectations. The models and the derived policies must be sufficiently simple and easy to understand to be trusted by the experienced MoE personnel in charge of the reservoir operations.

There have been several systems analysis-based simulation, optimization, or simulation–optimization methods utilizing linear programming (Mariño & Mohammadi 1983; Crawley & Dandy 1993; Watkins et al. 1999; Needham et al. 2000), nonlinear programming (Gagnon et al. 1974; Hiew 1987; Paudyal & Das Gupta 1990; Arnold et al. 1994; Lund & Ferreira 1996; Barros et al. 2003; Arunkumar & Jothiprakash 2012) deterministic and stochastic dynamic programming, and evolutionary or metaheuristic algorithms to optimize operation of reservoir systems from a deterministic single-objective single-reservoir to probabilistic multi-objective, multi-reservoir systems (Karamouz & Houck 1987; Sharif & Wardlaw 2000; Mousavi et al. 2004; Reis et al. 2005; Reddy & Kumar 2006; Brandi et al. 2018; Celeste & El-Shafie 2018; Ehteram et al. 2018). These methods have accounted for one to multiple different sources of complexity, e.g., nonlinearity, stochasticity, dimensionality, socio-economic, and sustainability issues, in both short-term and long-term planning of reservoir operations. They have been well reviewed by Yakowitz (1983), Yeh (1985), Wurbs (1993), Labadie (2004), etc. Among all several alternative techniques and modeling approaches, we propose a practical linear programming-based monthly optimization model capable of planning real-time operation of reservoir systems adaptively over a yearly time horizon while taking the long-term operation considerations into account. These types of model, that work based on the prediction of inflows over a short to medium planning horizon, are useful in integrating different purposes of multipurpose reservoirs (Nohara & Hori 2017).

Real-time models have a rich history in application to reservoir systems' operation. Dagli & Miles (1980) described a real-time operation method for determining operating policies for a set of four dams. In this work, a forecast was made at the beginning of each time step followed by a deterministic linear optimization model. Bras et al. (1983) proposed a real-time adaptive closed-loop control of reservoirs, where the objective was to minimize the losses due to deficits to different water uses and flood damages for the Aswan Dam case study. Mujumdar & Ramesh (1997) compared two types of real-time operation models for irrigation of multiple crops, i.e., standard and adaptive models, and showed the superiority of the adaptive real-time operation model. Xu et al. (2014) used an autoregressive integrated moving average (ARIMA) model for inflow prediction on a period-by-period basis to account for nonstationary inflows and combined it with hedging rules. Wang et al. (2012) addressed the issue of forecast uncertainty in flood control-based real-time multi-reservoir system operations using ensemble forecasts. They, however, assumed end-of-operation target water level a fixed already-known parameter. More can be found on standard real-time operation models' deriving policies or rules especially for flood control in the following studies (Wasimi & Kitanidis 1983; Unver & Mays 1990; Niewiadomska-Szynkiewicz et al. 1996; Hsu & Wei 2007; Chang 2008; Wei & Hsu 2008, 2009; Braga & Barbosa 2001;

Chou & Wu 2013; Ahmadi et al. 2014; Bolouri-Yazdeli et al. 2014; Liu et al. 2014; Chiang & Willems 2015; Nohara et al. 2016; Olofintoye et al. 2016). Additionally, long-term reservoir operation optimization models can provide useful information as target points that are used in short- and medium-term and real-time operation models (Ilich 2011; Ming et al. 2017). However, long-term considerations have not been explicitly accounted for in the context of real-time operation.

We propose a finite-horizon yearly real-time reservoir operation model in which the parameter of end-of-year reservoir storage volume, accounting for long-term considerations, is determined by a long-term optimization model, while this parameter is updated over the operation horizon. The developed model is a monthly forecast-based adaptive real-time reservoir operation model with a maximum one-year planning horizon for the operation of Boukan Dam reservoir regulating a major part of surface runoff of the basin. Having determined inflow forecasts, the real-time model is run at the beginning of each time step (month) and recommends optimal releases for all future months up to the end of the year. However, only the release for the current month is made, and the end-of-month reservoir storage is determined. Then, the inflow forecasts are updated, and the reservoir operation model is run again. This adaptive procedure is repeated every time step until the last month of the year. A long-term optimization model is also linked to the real-time model to provide it with the terminal end-of-year optimal reservoir storage at every decision time period while it moves forward. Combining an adaptive medium-term forecast-based real-time reservoir operation model and a long-term operation model through the parameter of end-of-year reservoir storage volume that is updated dynamically is an important and distinct aspect of the proposed methodology.

STUDY AREA

Lake Urmia water basin is located in the northwest part of Iran. The basin takes its name from Lake Urmia (LU) which is located at the center of the basin and suffers from a dramatic decline in its water level. In September 2015, the lake experienced 10% of its potential storage capacity, a situation that can get worse if major actions are not taken, that could culminate in total loss of the lake. The largest river in the basin is Zarineh-Roud River. This river starts from the Zagros Mountain range and drains to the LU. It passes through the three major states of Kordestan, West Azarbaijan, and East Azarbaijan and contributes to about 41% of total surface water inflow to the lake. The drainage area of Zarineh-Roud River is about 12,000 km^2, and it crosses two cities, Shahindej and Miandoab. Eight large dams are being operated that discharge water to the lake. Boukan Dam constructed on Zarineh-Roud is the largest dam in the basin, supplying water to agricultural, domestic, and industrial sectors. It has 810 million cubic meters (MCM) storage capacity and the long-term average inflow to its reservoir is about 1,700 MCM, while it has decreased to about 1,280 MCM during the last 15 years. Releases from the reservoir supply water to three important cities including Tabriz. They are also diverted at Norozlu to irrigate approximately 85,000 hectares of Miandoab farming lands.

The way the reservoirs are operated affects directly the amount of water received by the lake throughout a year. From another point of view, dams are being considered as one of the main causes of the lake shrinkage and its ecosystem degradation. The current situation of the lake has made the operation of the reservoirs more important than before and calls for new adaptation strategies including revised reservoir operation policies, considering their new role in supplying water for the lake when other demands, especially irrigation demands, have already increased significantly. In addition to the total volume of water releases, their temporal distributions have also been paid more attention. Releasing water for the lake in the irrigation season may not reach the lake as farmers could take the released water on the way towards the lake. On the other hand, storing water in the reservoirs before the irrigation season increases the risk of floods, whereas too early releases before the irrigation season could result in the risk of not being able to meet the irrigation demands. In such a complicated situation, the share of releases for the lake has always been sacrificed during the last two decades, something that must stop before the lake completely dries up.

In this study, we focus on the Zarineh-Roud sub-basin and the Boukan reservoir as the most important subsystems of the LU, draining and regulating more than 40% of the basin yield. Figures 1 and 2 illustrate the map of the LU

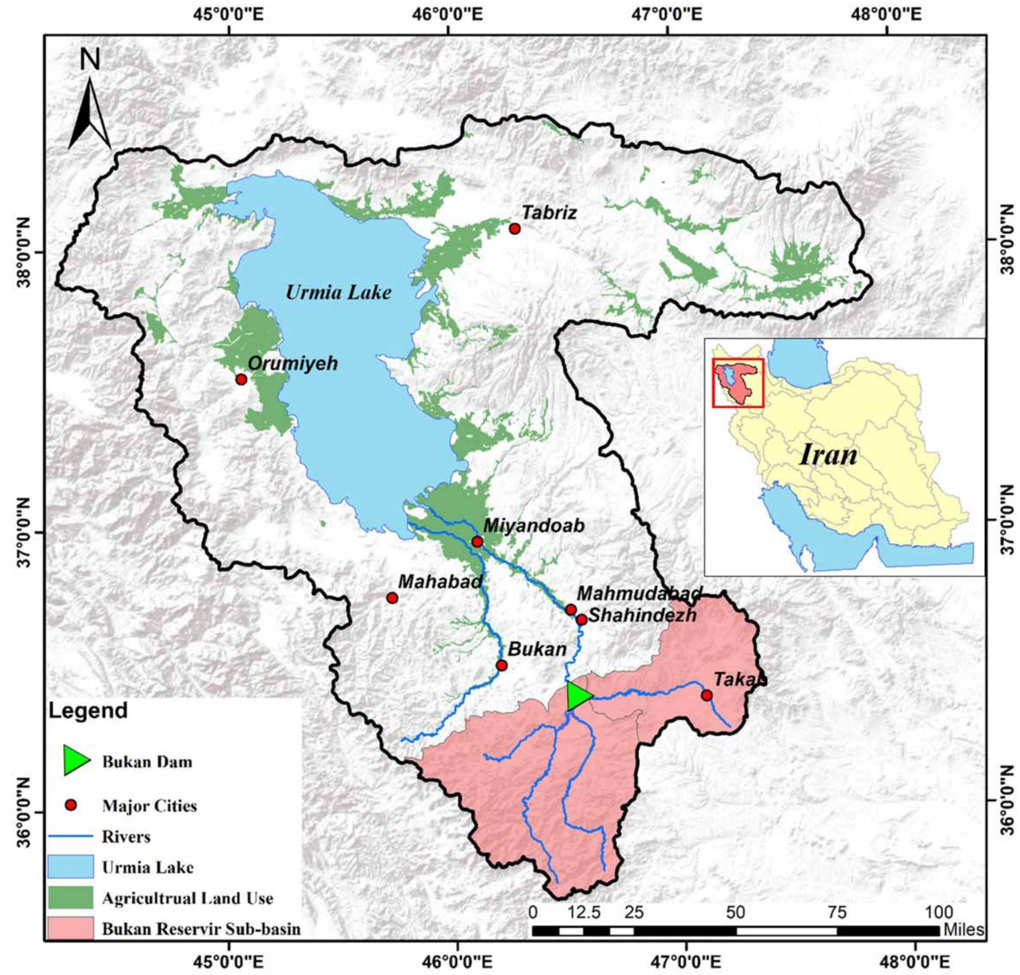

Figure 1 | Urmia Lake water basin located in the northwest of Iran.

basin and a schematic representation of the system components under study.

STREAMFLOW FORECASTING

Four data-driven approaches were employed to forecast inflows to the reservoir including k-nearest-neighbor (KNN), artificial neural networks (ANN), support vector machines (SVM), and adaptive neuro-fuzzy inference system (ANFIS). After training and testing these approaches, SVM and ANFIS with almost the same performances were better than other models, but ANFIS was slightly better than SVM. Since the focus of this paper is not on comparing different forecasting approaches, we only report the results obtained by the best forecasting model. ANFIS was trained, validated and used to forecast inflows to the reservoir from one to a couple of months ahead. It uses a combination of artificial neural networks and Sugeno-type fuzzy inference system (FIS) (Jang 1993; Jang & Sun 1997). Using a hybrid learning mechanism, consisting of the back-propagation gradient descent and the least squares algorithms, ANFIS determines the best possible set of both ANN and FIS parameters to map a given input–output set of data points. Thus, the model is a data-driven model that identifies the inherent function between certain input and output variables within a system without explicitly knowing the physical relationship between those variables.

Assuming two inputs, x and y, the equivalent ANFIS structure that derives the output will be a five-layer

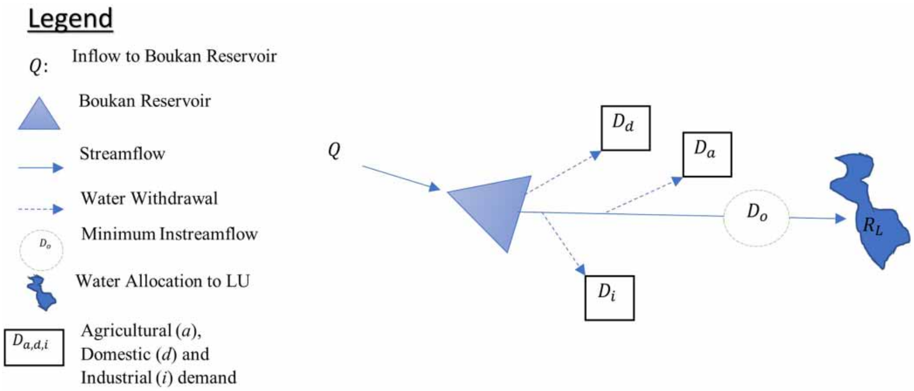

Figure 2 | Schematic view of Boukan reservoir system and its downstream components.

feed-forward network, shown in Figure 3. Considering these two inputs, the following type of rules are used in a Sugeno-type FIS (Wang *et al.* 2009):

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 A_1, A_2 and B_1, B_2 represent the membership functions of variables x and y, respectively. This part is referred to as the premise part and the parameters used in the membership functions are the premise parameters. For example, Equation (1) shows the Gaussian membership function with parameters a and b:

$$\mu(x) = \left[-\left(\frac{x-a}{2b}\right)^2\right] \tag{1}$$

Additionally, p_1, q_1, r_1 and p_2, q_2, r_2, are linear parameters in the consequent part, so they are called consequent parameters. Figure 4 shows the premise and consequent parts of the Sugeno FIS. In the ANFIS hybrid learning algorithm, the premise and consequent parameters are tuned in order to find the best mapping structure for the given input–output data. More detailed presentation of ANFIS for forecasting wind and hydrological time-series and reservoir operations can be found elsewhere (Ponnambalam *et al.* 2001, 2003; Nayak *et al.* 2004; Kazeminezhad *et al.* 2005; Keskin *et al.* 2006; Mousavi *et al.* 2007; Firat & Güngör 2008; Zounemat-Kermani & Teshnehlab 2008; Firat *et al.* 2009).

We use the ANFIS model to forecast future inflows to the Boukan reservoir. The basic statistics of the monthly inflows to the reservoir are presented in Table 1.

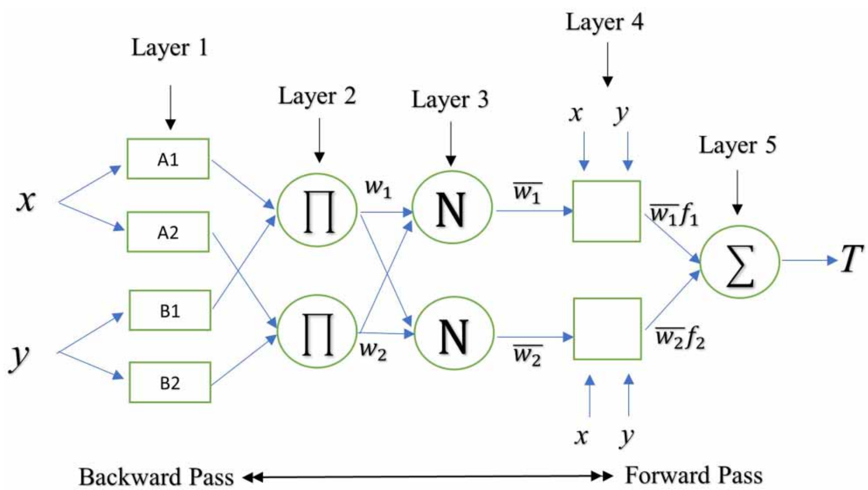

Figure 3 | ANFIS structure for a two-dimensional input vector x and output T.

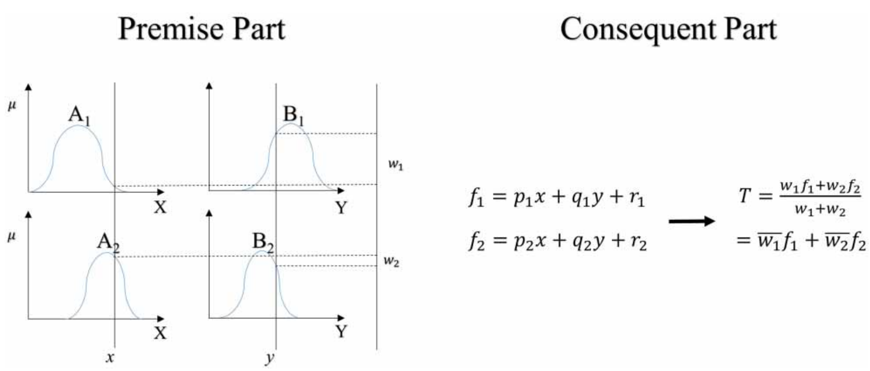

Figure 4 | Premise and consequent part of a Takagi-Sugeno fuzzy logic mechanism.

Table 1 | Basic statistics of monthly inflows to the Boukan reservoir (all values are in million cubic meters)

	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Yearly
Average	9.3	34.3	54.7	68.6	89.2	187.8	349.2	252.8	62.0	20.7	13.4	10.4	1,152.5
Std*	6.1	39.7	57.2	68.8	63.4	114.6	169.6	140.9	41.6	11.6	7.5	6.5	526.5

*Standard deviation.

Nearly 76% of total annual inflow occurs from February to May, making this period an important time window for storing water for the coming summer irrigation season. April has the highest average inflow and, at the same time, the highest risk of flood occurrence. Therefore, the reservoir storage volume at the beginning of April is of the utmost importance for preventing downstream from flooding.

To make a forecast of a future inflow to the reservoir at any time period t, one can consider inflow in period t a function of inflows in previous time steps, e.g., $Q_t = f\,(Q_{t-1}, Q_{t-2}, Q_{t-3}, \ldots, Q_{t-n})$. Therefore, the future unknown inflows are:

$$\begin{aligned} Q_{t+1} &= f(Q_t, Q_{t-1},\ Q_{t-2},\ \ldots,\ Q_{t-n+1}) \\ Q_{t+2} &= f(Q_{t+1}, Q_t,\ Q_{t-1},\ \ldots,\ Q_{t-n+2}) \\ &\vdots \\ Q_T &= f(Q_{T-1}, Q_{T-2},\ Q_{T-3},\ \ldots,\ Q_{T-n}) \end{aligned}$$

where n is the number of past inflows having a significant impact on the current period's inflow. Finding the appropriate value of n is important and, in fact, it determines the number of input variables to the ANFIS model. The larger n, the greater number of premise and consequent parameters will be, thus it increases the chance of overfitting. On the other hand, very low values of n may cause loss of valuable information and less accurate forecasts. We tested different values of n ranging from 1 to 7, and $n = 3$ was chosen to be the best value. Also, different number and shapes of membership functions were examined, and 11 Gaussian membership functions were finally considered in the final ANFIS model structure. The testing criteria chosen are coefficient of determination (R^2), Nash–Sutcliffe efficiency coefficient, root mean squared error (RMSE), and peak-weighted root mean squared error (PWRMSE) with respect to the validation data. From 35 years of available monthly data, the first 26-year set is considered for training, and the remaining nine-year set for validation.

Applying the ANFIS model, the best NSCE and R^2 values for the validation set as reported in Table 2 are 0.65 and 0.73, respectively. Higher PWRMSE as compared to RMSE shows that the forecast errors are larger for

Table 2 | Performance indices of ANFIS forecasting module

Index	Training set	Validation set
RMSE/$\bar{O}$[a]	0.6217	0.7252
NSCE	0.7979	0.6523
PWRMSE/$\bar{O}$	0.9789	0.9788
R^2	0.7979	0.7301

[a]$\bar{O}$ Average monthly inflow.

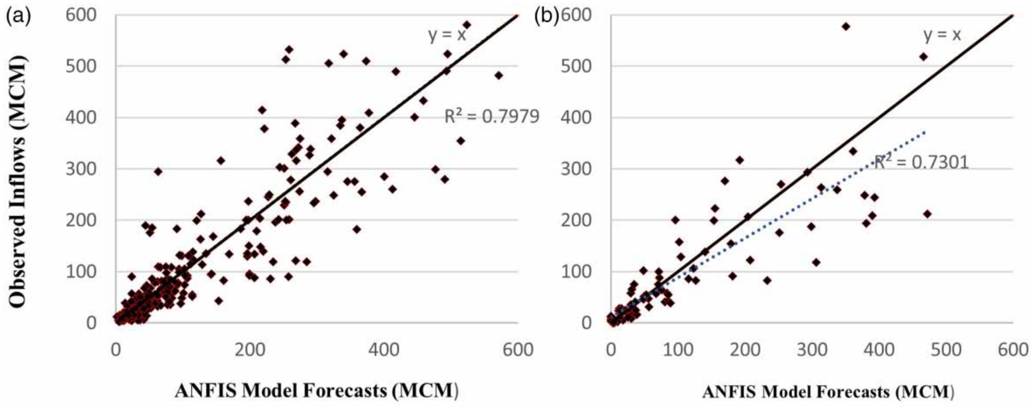

Figure 5 | Observed versus forecasted monthly inflows to the Boukan reservoir on (a) training set and (b) validation set.

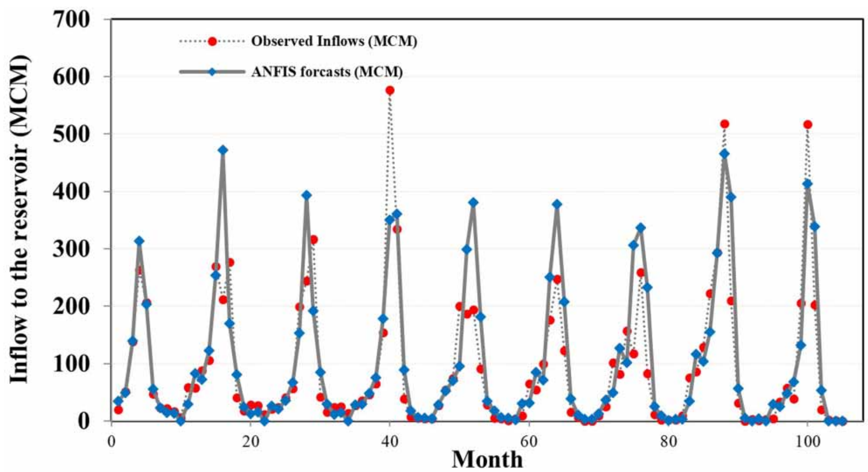

Figure 6 | Comparison of observed versus ANFIS forecasts time series on the validation data set.

higher-inflow months. Observed versus predicted-by-ANFIS inflows are shown in Figures 5 and 6.

We will use the best trained ANFIS model in the proposed real-time reservoir operation model framework presented in the next sections.

RESERVOIR OPERATION OPTIMIZATION

In this section, the formulation of the reservoir operation optimization model is presented. The formulation is used for both long-term and real-time operation with some differences and provides guidelines for the target reservoir storage levels at important decision times, such as the start time of releasing water for the lake and the beginning of the irrigation season.

The model's objective function is simply a priority-based weighted sum of water allocations to environmental flow requirement of Zarineh-Roud River downstream of the dam, irrigation, and Lake Urmia, respectively. The minimum values for these three water uses and their priorities (weight coefficients) were agreed upon among the main parties involved, i.e., MoE, MoAJ, National Environmental Organization and ULRP. In line with this, although water allocation to the irrigation sector as the main water consumer has been given a higher priority than releasing water for the lake, the irrigation water demand values are considered based on the agreed-upon plan of 40% reduction in irrigation water allocation in five years, as explained in the Introduction. Therefore, the irrigation demand here is the reduced demand based on the agreement, something that has already imposed meaningful stress on the agriculture sector and farmers. Additionally, water allocations to the lake have been considered separately, independent of the water released for the non-consumptive instream flow uses. Therefore, the priority rankings are associated with environmental instream flow, irrigation, and the lake as reflected in the following objective function:

$$Max\ Z = \sum_{t=1}^{n} C_o R_{o_t} + C_a R_{a_t} + C_L R_{L_t} \tag{2}$$

where n is the total number of time steps, C_o, C_a, and C_L are, respectively, the priority coefficients for water allocation to Zarineh-Roud River's minimum environmental flow, irrigation, and Lake Urmia demands, and R_{o_t}, R_{a_t}, and R_{L_t} are volumes of water allocated to those demands, respectively. The constraints set, i.e., Equations (3)–(8), include water balance equations, upper bounds on the allocation values that are equal to demands, constraints regarding storage and discharge capacities of the reservoir and the downstream river, especially at the inlet of Lake Urmia where fuse plugs are located for conducting the released volumes to the body of the lake and preventing them from being lost by seepage and evaporation.

$$S_1 \leq S_n \tag{3}$$

$$S_{t+1} = S_t + Q_t - R_{a_t} - R_{d_t} - R_{i_t} - R_{o_t} - R_{L_t} - E_t - spil_t \tag{4}$$

$$Ra_t \leq Da_t, \quad Rd_t = Dd_t, \quad Ri_t = Di_t, \quad Ro_t \leq Do_t \tag{5}$$

$$R_{L_t} + R_{o_t} \leq Cap_{fuze} \tag{6}$$

$$S_{min} \leq S_t \leq S_{max}, \quad R_{min} \leq R_t \leq R_{max} \tag{7}$$

$$\frac{R_{at}}{D_{at}} = \frac{R_{a_{t+1}}}{D_{a_{t+1}}} \text{ for } t = 0, n-1 \tag{8}$$

where Q_t, E_t, and $spil_t$ are inflow, evaporation, and spill volumes in period t, respectively, and S_t is the reservoir storage volume at the beginning of period t. Do_t, Da_t, Dd_t, and Di_t are, respectively, minimum environmental, irrigation, domestic, and industrial demands. Cap_{fuze} is the capacity of fuse plugs. Equation (8) ensures when the total annual irrigation demand cannot be met, shortages are proportionately distributed over different months of the irrigation season (Ilich 2011).

Optimum reservoir releases and storages can be determined given the historical inflows to the reservoir and specified demands. Ilich (2011) used the above model for long-term operation of reservoir systems, based on which reservoir rule curves were determined for different anticipated supply conditions and starting storage levels. In his proposed approach, time series of optimum reservoir storages are obtained first by solving the above model; then the probability distribution of the reservoir's end-of-month (EoM) storage volume is determined for each month. For example, having N years of monthly data, there are N optimum EoM storages for each month, each corresponds to a certain amount of yearly inflow, from which the probability distribution of reservoir storage can be estimated. Then by connecting the optimal reservoir storages of different months at a certain probability (reliability) level, the storage rule curve for that particular probability level is obtained. Having knowledge of these rule curves, one can use them as end-of-month target storage levels in real-time operation. The above model is solved first over a long-term horizon to determine the end-of-year optimal terminal storage values associated with different probability levels of yearly inflow to the reservoir. These end-of-year storage volumes are then used as one of the input parameters to all medium-term operation models within a forecast-based adaptive real-time operation framework as explained in the following section.

ADAPTIVE REAL-TIME OPERATION MODEL (ARTOM)

The proposed framework for ARTOM of a reservoir system consists of three modules. First, the forecasting module predicts the monthly inflows to the reservoir for the entire time horizon, which is one year in this study. Calculating the yearly inflow forecast by summing the monthly forecasts up, the probability level of yearly inflow forecast to the reservoir will be determined using the cumulative probability distribution function of the annual inflow variable. Afterwards, knowing the optimal rule curves obtained by the long-term optimization model at different reliability levels and the determined probability level just explained, one can read the optimal end-of-year reservoir storage as an input parameter to the ARTOM.

Adaptive decision-making is, on the other hand, another important feature responding to future changes and uncertainties in both supply (inflows) and demands. For each month t, upon the next T–t months inflow forecasts, obtained by the forecasting module, and the terminal end-of-year storage, derived from the long-term optimization model, the reservoir operation optimization model is run to determine optimal releases, storages, and water allocations to each water use sector for the next T–t months. However, we know that the accuracy of inflow forecasts diminishes nonlinearly as the forecast lead-time increases. For example, if we are currently at the first-time step $t = 1$, the forecasting module predicts the inflows for the next $T = 12$ months although the forecasted inflows may not be as accurate as they should be for a few months after t. Therefore, only the optimal release for month t is applied. Then the system state goes to the beginning of month $t + 1$ when all inflow forecasts for months $t + 1$ to T as well as optimal terminal end-of-year storage volume are updated (updating module). Subsequently, the reservoir operation optimization model is run again under the updated future inflow forecasts and the terminal reservoir storage volume. This procedure moves forward up to the last stage when $t = T$. Figure 7 demonstrates the flow diagram of the ARTOM, its different modules, and their interactions. Since the future inflow forecasts are updated at the beginning of each month, the estimated total annual inflow changes in every month, so the terminal end-of-year storage level should also be updated month by month as the procedure moves forward.

Note that in the proposed ARTOM, the notion of 'adaptive' means repeatedly updating and recalculating inflow

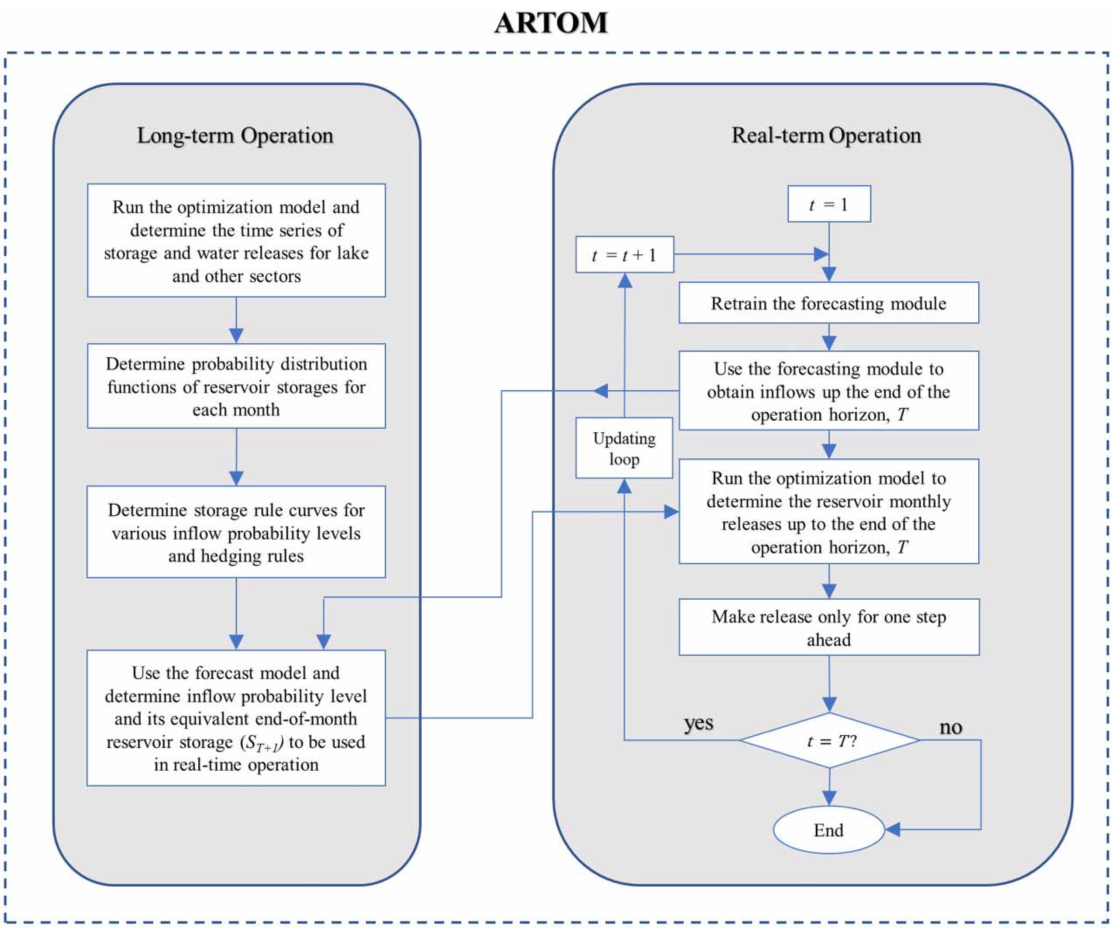

Figure 7 | Flow diagram of the real-time operation model.

forecasts, terminal reservoir storage volume, and release control actions along with receiving newly available information. Therefore, it does not mean that the dynamics of the operation model changes adaptively too.

RESULTS AND DISCUSSION

General results

The proposed real-time operation model is a framework to assess the operation of Boukan Dam reservoir as the largest and most important regulating hydro-infrastructure in the basin, operation of which significantly impacts the annual water feeding the LU. Figure 8 shows the rule curves associated with different exceedance probability levels of annual inflow. These curves have been derived from the optimal time series of storage volumes determined by the long-term optimization model. As expected, the figure shows that in years with annual inflows greater than normal (lower exceedance probabilities), higher storage volumes result. Additionally, during the spring season when more than 70% of annual inflow occurs, the reservoir storage level is higher than that in other seasons. Specifically, the storage level at some time about the end of April, i.e., beginning of the irrigation season, is of vital importance. Note that most irrigation demand is in summer months when less than 7% of the annual inflow is realized, thus it is essential to retain water in the reservoir in advance to be released in summer to meet downstream water demands. This figure also reveals that it is not optimal to release all available water and bring the reservoir storage to its minimum possible operating level at the end of a year, so the end-of-year (EoY) storage level is not usually equal to the minimum storage level. This result is contradictory to the expectation of some experts in ULRP who believe since the reservoir has not been designed as a carry-over regulating element, all available excess water should be released for LU. However, the best storage level depends on the amount of annual inflow. We clearly see the range within which this input parameter to the real-time model varies.

The ARTOM is tested on the last nine years of available data. This nine-year period, containing dry, normal, and wet years, has not been used in deriving long-term rule curves, so it is considered only for validation purposes. To assess how well the proposed real-time approach performs, we need to have a benchmark. In this vein, we first run the optimization model for the nine-year period assuming that we have perfect foresight on future inflows. In such an ideal situation, the optimization model (ideal operator) knows everything about what future inflows will be without any forecast error or uncertainty. Therefore, the model solution and its objective function is the best possible solution that one

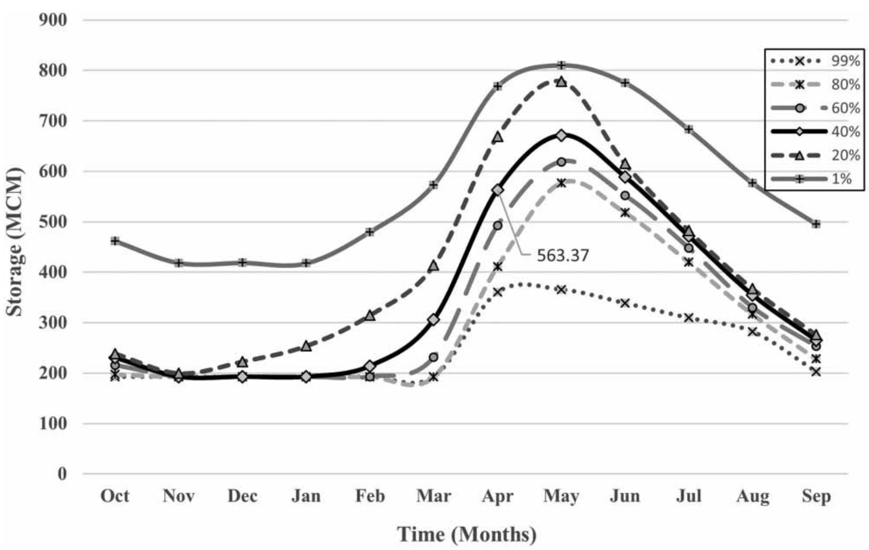

Figure 8 | Optimum rule curves for various probability levels of annual inflow derived from the long-term optimization model.

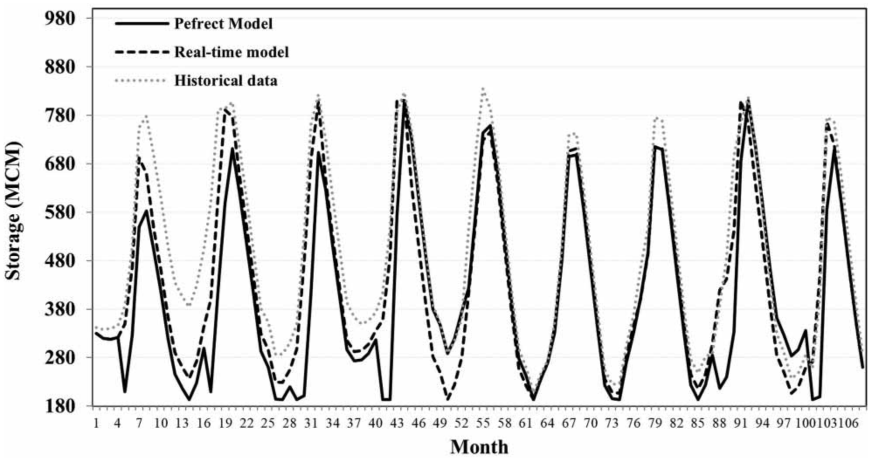

Figure 9 | Comparison of reservoir storage volume time series for perfect foresight, real-time, and historical operation conditions.

could obtain with which any other solution can be compared. Figure 9 shows the storage volumes determined by the perfect and real-time models as compared with those realized in historical operation of Boukan reservoir over the studied nine-year period.

In Figure 9, the perfect (ideal) model's storage volumes are lower than those of other models, especially the historical operation case, while it has been able to meet the downstream demands perfectly. The storage time series of the real-time model is slightly higher because every year it must be more cautious about meeting summer irrigation demands. Consequently, it retains more water in the reservoir before starting the irrigation season. This is more evident in the first four years with above-normal inflows, whereas the storage volumes are very close to those of the ideal model for a dry period from 2012 to 2015. In this dry period, although reservoir storage volumes resulting from the ARTOM are lower than historical ones, the real-time model has still been able to meet downstream irrigation demands at a reliability level of 98.6%.

Table 3 compares objective function values (weighted sum of three water allocation volumes), uncontrolled spill volumes, and allocated-to-LU release volumes for the mentioned three cases. As expected, the ideal perfect model

Table 3 | Comparison of results for perfect foresight, real-time, and historical operation conditions with respect to spillage, objective function value, and the release volume for LU

	Uncontrolled spillage*			**Objective function**			**Releases for LU***		
Year	**Historical data**	**Perfect model**	**Real-time model**	**Historical data**	**Perfect model**	**Real-time model**	**Historical data**	**Perfect model**	**Real-time model**
2016–17	230.2	0.0	0.0	5,509.6	7,115.9	6,731.8	333.5	424.5	347.7
2015–16	647.9	0.0	49.0	5,634.7	8,583.7	8,829.4	713.1	654.4	705.6
2014–15	131.7	0.0	0.0	5,526.9	5,683.2	5,540.7	51	59.9	76.3
2013–14	0	0.0	0.0	5,694.7	5,899.4	5,638.8	29.024	11.2	0.0
2012–13	175.1	0.0	0.0	5,873.9	6,596.1	6,193.3	36.008	127.4	54.2
2011–12	680	0.0	191.1	4,838.4	7,337.9	6,965.3	52.143	527.6	453.0
2010–11	242.7	0.0	0.0	5,196.5	6,822.2	6,904.7	8.683	240.1	256.6
2009–10	238.9	0.0	0.0	6,366.9	7,796.9	7,840.7	1.04	201.7	210.5
2008–09	39	0.0	0.0	5,258.7	6,548.5	6,311.3	0.74	139.3	99.0
Average	265.1	0.0	26.7	5,544.5	6,931.5	6,772.9	136.1	265.1	244.8

*All values are in MCM.

has caused no uncontrolled spill as it knows everything about future water availability, so it has been able to make pre-releases and prepares enough empty storage prior to incoming floods. The real-time model's performance is also acceptable with 191 and 49 MCM spilled volumes in very wet years (2011–2012 and 2015–2016). Having these spill volumes compared with 680 and 648 MCM that occurred in these two years of historical operation, it reveals that the real-time model performs quite well in terms of avoiding unwanted spills. Knowing the historical releases and water allocations from the MoE data base, the objective function value corresponding to historical operation can also be calculated. It is notable that the real-time model's objective function value is only 2% less than that of the ideal model's objective function benefiting from perfect foresight on future inflows, whereas it is 22% better than the simulated objective function value of historical operations. Finally, one of the desired goals of the restoration program has been releasing water for LU as much as possible. In this regard, the average annual water released for the LU resulting from the real-time model is 265 MCM as compared to 245 MCM obtained by the ideal model. It shows that the real-time model performs satisfactorily in allocating water to LU while fulfilling other demands, especially irrigation demands, almost the same as a perfect model does. On the other hand, only 136 MCM per year has been allocated historically to the LU. This means that the real-time model has increased the share of LU about 80% compared to that in historical operations.

Results on the adaptation mechanism

Another important point of interest is to analyze how the adaptive procedure incorporated in the real-time model helps us reduce the negative effect of the forecast uncertainty. As we explained, the real-time model benefits from an updating module re-evaluating future inflow forecasts, the terminal EoY storage level, and future releases (storages) at the beginning of each time step. In other words, the optimization model solutions are applied just for the immediate next time step, and the solutions for other future months are left to be re-evaluated later after realizing other incremental information on future inflows. Such an adaptive procedure helps the model keep the negative effect of propagating uncertainty of longer-lead forecasts as reduced as possible. Now we want to quantify and show how the adaption procedure does such a job. This feature can be looked at from two aspects: (1) how an inflow forecast for a future month far enough from the current month varies during the adaptation process, regardless of the reservoir operation optimization model and (2) what the variation of that future month's reservoir release looks like during the adaptation mechanism employed in the real-time operation optimization model. The most important months in terms of their influence on the performance of the real-time operation model are months February, March, April, and May, during which, more than 75% of the total yearly inflow typically occurs. They are also all before the irrigation season, so there is still opportunity during these months to make releases for the LU, and at the same time, these months are important with respect to the purpose of flood control.

Figure 10 shows the percentage error in inflow forecasts for the mentioned important time window (February to May) for a normal year (2010–2011). At the beginning of the first month (October), the forecast errors are between 72% (for May) to 15% (April). However, Figure 10 illustrates how forecast errors are decreasing while heading toward these particular time periods. For example, the forecast error for the month of March, when there is still enough time to react to likely droughts or floods, are 20, 14, 5, and almost 0% at the beginning of the months from October to February, respectively. This shows how well the adaptation of inflow forecasts performs.

Now let us see how well the real-time model works under an adapting forecast uncertainty condition. As mentioned before, the perfect ideal model will provide us with the best possible release (storage) values for every decision variable. Therefore, the updating procedure, in fact, does its best to be as close as possible to such an ideal situation. Therefore, we compare the real-time model solutions (releases) with those obtained by the ideal model. Figure 11 shows the differences between reservoir releases made for the LU during the months of the mentioned window at the beginning of different months as compared to those of the perfect model. We can see in this figure how reservoir releases converge or vary around their ideal values as a result of the adaptation process. In fact, the final releases suggested by the real-time model during the mentioned four-month period

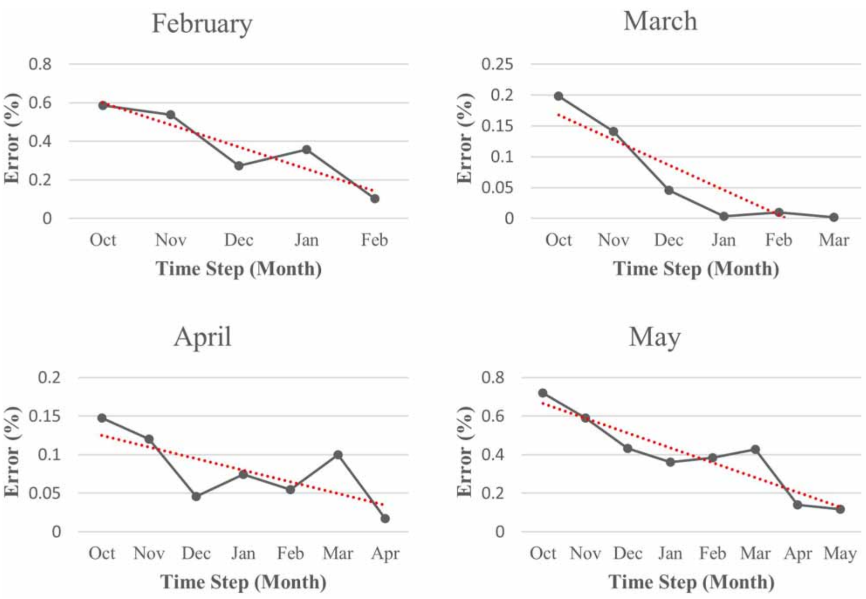

Figure 10 | Trend of ANFIS model forecast errors for a period from February to May in a normal year (2010–2011) at the beginning of different months prior to the period.

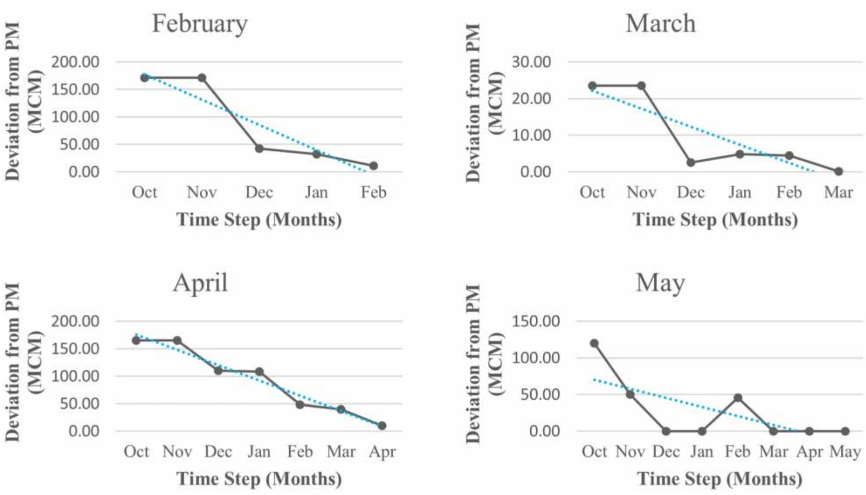

Figure 11 | Difference between the reservoir releases made for LU obtained by the proposed real-time model and the perfect model for a period from February to May in a normal year (2010–2011) at the beginning of different months prior to the period.

are within 5% of the ones proposed by the ideal model. This shows how satisfactorily the adaptive procedure incorporated in the proposed real-time model performs in coping with the uncertainty of future inflow forecasts.

Comparison with an alternative operation model

In our proposed real-time adaptive operation model, the optimum rule curves derived by the long-term optimization model are used to determine the optimal terminal EoY reservoir storage as an input to the real-time model. The rule curves can also be used to simulate the reservoir operation using the target EoM storages derived for all months. The purpose is to assess how well the optimization method incorporated in the operation module performs compared to a simulation approach that uses predefined optimum rule curves derived by a long-term optimization model. To do so, having known the probability of occurrence of inflow, we can obtain optimum EoM reservoir storage volumes from Figure 8. For example, let us assume that the yearly inflow forecast at the beginning of April is 1,231 MCM. The probability of occurrence for this inflow is 40% (black line in Figure 8) in which the EoM storage volume for the month of April is 563.4 MCM. Therefore, the total release in this month and water allocations to different uses including the share of LU can be determined. For instance, if there is any shortage in meeting higher-priority demands (instream flow and irrigation), the shortage will first be allocated to irrigation and then to environmental flow. In this situation, no water will be allocated to the LU. Subsequently, the annual inflow forecast will be updated at the beginning of the next month (November) based on the realized inflow in October, and the procedure, referred to as real-time simulation model (RTSM) hereafter, moves forward over time.

The RTSM explained above has been tested over the nine-year validation period. The resulting reservoir storage time series has been presented and compared with those of the perfect-forecast model and ARTOM in Figure 12. In this figure, the storage volumes resulting from ARTOM are lower than those of other models. The reliability levels of meeting irrigation and environmental demands and the water allocated to LU resulting from the ARTOM and the RTSM are compared in Figure 13. The ARTOM has successfully met the downstream demands in all years at a perfect reliability level equal to 1, whereas for the RTSM, the average annual reliability levels in meeting irrigation and environmental demands are 77.1 and 82.6%, respectively. This is somewhat unacceptable in terms of the system's operation purposes where the minimum instream flow and reduced irrigation demands have to be met as agreed-upon goals. Nevertheless, the RTSM allocates water to LU 62% more than ARTOM with an average annual share of 397 MCM.

SUMMARY AND CONCLUSIONS

A real-time adaptive forecast-based model was proposed for the operation of Boukan Dam reservoir constructed on Zarineh-Roud River in Lake Urmia (LU) basin. The model consists of three modules of streamflow forecasting, reservoir operation optimization, and updating. The incentive for this modeling attempt is to better meet the water demands of LU, a vital ecosystem resource that is drying out. Evaluating the performance of the proposed model over a nine-year test period, it proved to be efficient in terms of meeting downstream domestic and irrigation demands, prevention from flooding, and making more releases for LU in a timelier manner. It showed a performance very close to that of an ideal operation model benefiting from perfect foresight on future water availability without any uncertainty. The key to the success of the proposed methodology is the adaptation to changes and uncertainties. We cannot delete the forecast uncertainty, but we do cope with it by receiving feedback and updating the decisions as more information becomes available. In

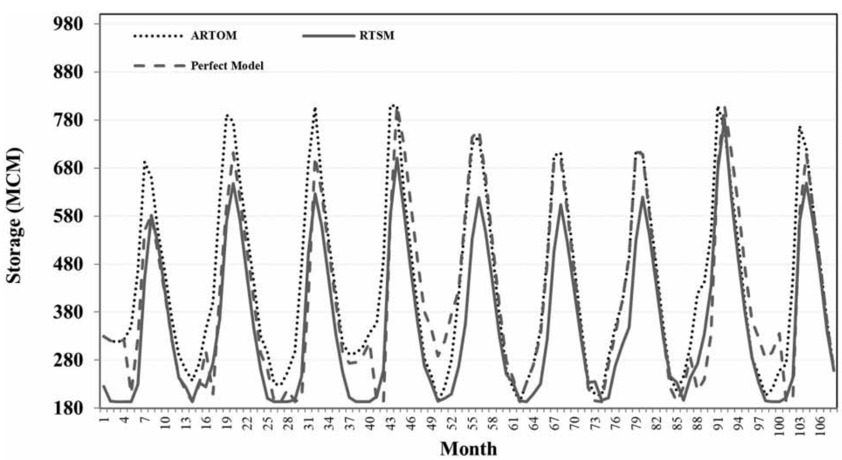

Figure 12 | Comparison of reservoir storage volume time series for perfect ideal, real-time adaptive optimal operation, and real-time simulation operation models.

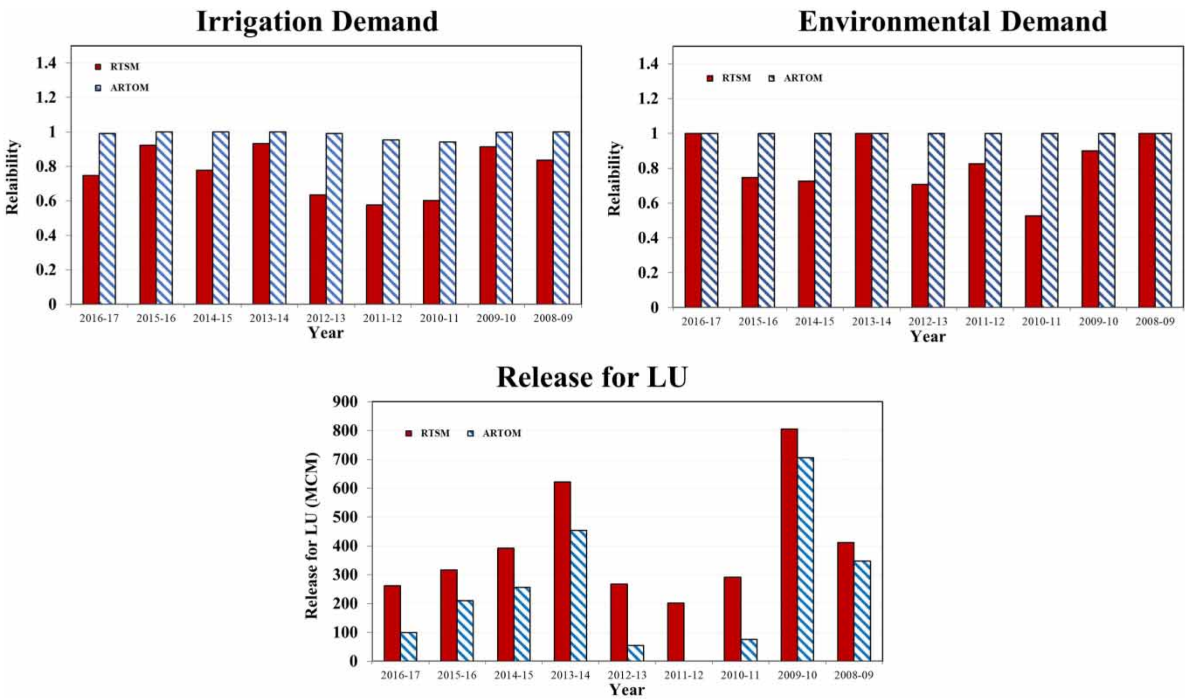

Figure 13 | Comparison of reliability levels in meeting irrigation and environmental demands and releases made for Lake Urmia for adaptive real-time operation and real-time simulation operation models.

this regard, we demonstrated quantitatively how the proposed adaptive procedure is able to reduce inflow forecast errors and uncertainties and the corresponding reservoir releases as it moves forward and receives more information on future inflows to the reservoir. Although the model accounts for both medium- and long-term objectives, it is computationally efficient and easy to use in real-world practical applications, making it suitable to be extended to multi-reservoir systems. This is because the linear long-term optimization model is run just one time, and its results are encapsulated in a set of rule curves conditioned on yearly inflow forecasts. These rule curves and inflow forecasts are then utilized within the real-time operation framework, based on which the optimal end-of-year reservoir storage volume is determined and updated on a period-by-period basis.

Despite the proposed methodology being general, we only considered adaptation to changes and uncertainty in the supply side, and downstream water demands were assumed to be known. The methodology should be extended in future works to account for doing the same for irrigation and ecosystem water demands. The developed model can be linked to a hydro-economic-ecologic water allocation mechanism to study the downstream subsystem in a more detailed way considering stakeholders' participation and preferences.

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