Drought Mitigation through Long-Term Operation of Reservoirs: Case Study

Mohammad Karamouz¹ and Shahab Araghinejad²

Abstract: Dealing with climate variability in a river basin presents many challenges in managing a water resources system. Occurrence of severe and persistent droughts deplete reservoirs storage to critical levels, which may lead to future water supply disaster. This paper illustrates certain benefits of using long-lead streamflow forecasts as well as restriction rules for reservoir operation to help manage the water resources system in the Zayandeh-rud River Basin in Iran. An approach is developed for activating restrictions on allocating water to agricultural demands during a drought and predicting low flow regimes using long-lead forecasts. The long-lead forecasts could utilize valuable hydroclimatic information such as the El-Nino southern Oscillation and northern Atlantic Oscillation to predict seasonal streamflow values. Hedging rules for optimal water supply releases is developed based on the benefit functions of release and carryover storage at each agricultural season. Hedging rules are triggered by different levels of drought indices determined by the predicted water availability at the beginning of each agricultural season. The method is used on an historical data set of hydroclimatic variables of the system to simulate the real-time operation of the Zayandeh-rud Reservoir. The utility of the method is demonstrated for operating the Zayandeh-rud Reservoir from the drought mitigation point of view. Furthermore, the proposed model is compared to a stochastic dynamic programming model by investigating different indices such as drought duration, drought severity, drought loss, and reliability of agricultural water demands allocation. The results indicate that the use of the proposed approach can significantly reduce the vulnerability of the system during hydrological droughts and increases the long-term benefits of agricultural water demand allocation.


CE Database subject headings: Droughts; Reservoir operation; Forecasting; Iran; Water resources.

Introduction

Drought is known as a deficiency of water in one or several components of the hydrologic cycle. Extent and magnitude of this deficiency define the characteristics of a drought event, namely duration and severity. Drought could be a creeping disaster, which can last for many years, and could have devastating effects on water and agriculture resources. It is known as the most destructive climatic extreme event among other events such as floods, tornados, and hurricanes, which causes both natural environmental and social damages (Riebsame et al. 1991; Kim and Valdes 2003).

There are three well-known types of droughts: meteorological, hydrological, and agricultural, according to the deficiency in rainfall, water supply, and soil moisture, respectively. Hydrological drought is defined as the inability of a water resources system to supply proper water demands. Hydrological drought is caused by meteorological drought and is followed by agricultural drought. In short-term drought management, the severity of a hydrological drought could be reduced by supply/demand management through delivery restrictions, augmentation of water availability by lower quality or by greater cost than ordinary sources, and making better use of available water resources by optimizing operating rules. The ability of a water supply system to face a drought could also be improved through long-term management such as construction of infrastructures, reduction of water distribution and water use losses, and reuse of wastewater (Wilhite et al. 1987). This paper deals with the short-term mitigation of drought through appropriate surface reservoir management.

A water manager needs quantitative drought triggers to activate the onset and extent of some restrictions that should be utilized. A drought trigger is typically a specific value of some indices, more useful than basic data, for decision making. Although none of the major drought indices is inherently superior to the rest in all circumstances, some indices are better suited than others to certain climates and applications. Predicted inflow and the available volume of water storage are suitable drought indices for a water supply system. These indices are dependent on both hydrological and climatological characteristics of a region through inflow to the reservoirs.

Many investigators have improved the methods of drought monitoring and prediction to make water resources systems operation more efficient. Lohani and Loganathan (1997) used a decision tree framework in issuing drought warnings. They used probability of future Palmer drought severity index (PDSI)-based weather classes along with cumulative precipitation shortage to provide each meteorological/agricultural drought state for a particular month. Kim and Valdes (2003) used a conjunction of
wavelet transforms and neural networks to forecast the PDSI in the Conches River Basin in Mexico for up to 6 months. Karamouz et al. (2004) investigated the variation of PDSI to monitor onset and termination of drought in the Zayandeh-rud River Basin in Iran.

As proposed by Shih and ReVelle (1995) common drought management steps are as follows: (1) forecasting of inflows and demands; (2) consideration of drought management options; (3) establishment of levels of indicators that trigger the various options of a demand reduction program; and (4) adaptation of a management plan at the levels indicated by drought indices. Shih and ReVelle (1994, 1995) developed continued and discrete hedging rules for a single water supply reservoir. They formulated linear and nonlinear mixed integer programming models that minimized the maximum deficit and maximized the number of months when no water rationing is required. Chang et al. (1995) developed a model to use flood-control reservoirs for drought management in the Scioto River in central Ohio. They defined different levels of drought indicators (e.g., streamflow, precipitation, temperature, groundwater, and reservoir elevations) to distinguish drought events from a normally experienced historical record. Tu et al. (2003) developed multireservoir mixed integer linear programming for optimizing a large-scale regional water distribution system, considering rationing rules during droughts.

Most of the previous works on the drought management of the Zayandeh-rud Basin in Iran have been focused on the investigation of the characteristics of historical drought events, which have already been experienced in the basin. They do not provide a methodology for mitigating the anticipated droughts in the basin. Despite the significant role of the Zayandeh-rud Reservoir in the surface water resources management of the basin, there have been no strategic policies for operating the reservoir from the drought mitigation point of view. The present study deals with the development of a long-term operation model for the Zayandeh-rud Reservoir. The work addresses the problem of coupling long-lead streamflow forecasts and strategic rules of long-term operation for the surface reservoir. Although the forecasting method and the reservoir operating model applied in this study have been well defined in previous works, conjunctive use of these models in the case study is unique. The main contribution of the present study is developing a procedure for selection of operating rules to address the long-term operation problem of a reservoir. An algorithm of combining different analyses and methods is presented and this algorithm is used to derive some rationing rules for the surface reservoir operation to mitigate drought impacts. A key objective of this study is to show the effect of applying long-lead forecasts as well as hedging rules to mitigate the impact of hydrological drought in the Zayandeh-rud Basin.

Reservoir Operation in Anticipation and during Drought

The proposed approach of this study is based on an adaptive generation of seasonal release policies using hedging rules, where input and output data are readjusted every season based on new initial conditions of the system and predicted inflows. This approach is illustrated in Fig. 1. As it is shown in this figure, operating a reservoir when anticipating and during a drought requires two major models: long-lead forecasting and optimal hedging rules. Also a range of data including hydroclimatological time series, characteristics of the system, and the drought loss information are used in different analyses of this approach.

Using a forecasting model, inflows to the reservoir are predicted. Triggers are calculated using the water currently available in the reservoir plus the expected value of future inflows to the reservoir. Restriction rules are activated upon feedback from the triggers. Optimal release and the target storage are calculated at each time step. More details are described in the following sections.

Streamflow Forecasting

Nonparametric regression methods are used to forecast seasonal inflow to the reservoir and to estimate the most probable streamflow trace for each forecast instant.

For each forecast instant $t$, let $P_i^n$, $(j=1,2,3,\ldots$ number of predictors) be an $n$-dimensional feature vector of past streamflows $(I_t)$. To estimate streamflow in time $t$, $I_t$, the forecasting method imposes a metric on the vector of current predictors $(P_t^j)$ to find the set of $K$ past nearest neighbors. $K$ number of past streamflows $(I_t)$ that have the minimum norm are obtained, $\|P_t^j-P_t^n\|$ among all candidates. The most widely used metric to identify neighbors is the Euclidean norm which, for an $n$-dimensional feature vector, is calculated as

$$d_{ij} = \|P_t^j-P_t^n\|^2 = \sum_{i=1}^{n} (p_{ij} - p_{jn})^2 = \sum_{i=1}^{n} (p_{ij} - p_{jn})^2 + \cdots + w_{m}(p_{in} - p_{jn})^2$$

where $w_n$ = weight of $n$th predictor.

Then, $m$-stepahead forecast, $I_{t,m}$, is obtained by using the following equation:

$$I_{t,m} = \sum_{j=1}^{K} \lambda_j f_{j,m}$$

where $\lambda_j$ = weight of the $j$th observed dependent value (historical streamflow); and $K$=number of neighbors.
In the K-nearest neighbor (K-NN) methods, a kernel function is simply used to calculate \( \lambda \) weights. In this study, using the kernel function proposed by Lall and Sharma (1996), \( \lambda \) weights are calculated as

\[
\lambda_j = \frac{1}{\sum_{i=1}^{K} 1/j} (1/j)
\]

where \( j \) = order of the nearest neighbors in which the nearest have the lowest \( d_j \) (\( j = 1 - K \)).

In the K-NN method, the weights of predictors (\( w_x \)) and the number of neighbors (\( K \)) that produce the lowest mean square error of forecasting are found by computing the error for all combinations of weights and \( K \) values through cross validation of the calibration data set. In the process of cross validation, streamflow is estimated by the observed data for each set of \( w \) and \( K \) at each time in turn excluding the observed streamflow at that time. Then, the parameters which result in the least mean square error of forecast are used as the optimal parameters.

Using geostatistical analysis, Aragheinjed et al. (2006) proposed a new method of calculating \( \lambda \) weights in Eq. (2), called geostatistical-based procedure of forecasting (GBPF). The GBPF results in better forecasts than K-NN since, in contrast to K-NN, GBPF considers a variable number of neighbors and uses a more robust procedure to calculate the weights of neighbors. In this study, the GBPF method is used for estimating streamflow forecast for 6 months ahead. However, the results of the GBPF tend to be the results of a simple K-NN method when the uncertainty of forecast estimation rises. Therefore, the K-NN method is used to estimate streamflow traces for more than 6 months ahead without compromising the forecast accuracy of GBPF. The use of K-NN for estimating streamflow traces (streamflow sequences for more than 6 months ahead) has the advantage of avoiding the computational efforts of using the GBPF.

**Hedging Rules**

Water supply managers prefer a number of smaller shortages compared to a few very large ones, suggesting that damages are convex in the shortfalls (Shih and Revell 1995). In the general situation of actual drought, realistic reservoir management rules would suggest that during periods of incipient drought, reductions be made in demand even if it can be fully delivered from storage and current inflow. This reduction prevents larger shortages in later periods of operation. The minimization of total shortfall as it is the objective of so-called standard operating policy is not the objective of water managers regarding the convexity of shortage losses during droughts (Hashimoto et al. 1982). To minimize the impact of current and consequent droughts, reservoir operation rules are coupled with the hedging rules to balance the shortage with the carryover storage and to ensure that a sufficient amount of water remains in the reservoir for the following period of water supply. Decision makers in water resources systems must evaluate the tradeoffs among immediate and future use of water before the future state of supply is known. In the face of this uncertainty, forecast of future streamflow can be helpful in planning the operation. Anticipation of and during a drought, streamflow forecasts would be more valuable. The potential value of these forecasts to water resource systems operation is significant if there are modeling techniques and decision processes available to explore them (Faber and Stedinger 2001).

Consider a single reservoir system. The continuity equation for the reservoir can be written as follows:

\[
S_t + I_t - R_t - E_t = S_{t+1}
\]

where \( S_t \) = beginning storage during time period \( t \); \( S_{t+1} \) = ending storage during time period \( t \); \( I_t \) = inflow during time period \( t \); \( E_t \) = total loss during time period \( t \); and \( R_t \) = release during time period \( t \). Storage \( (S) \) plus forecast inflow \( (I) \) = common variable for a drought index in hedging rules. During operation of the reservoir, hedging rules are activated, when drought indices (say \( S_t + I_t \)) get to specific values called drought triggers. In general, during each time period \( t \), the relationship between the drought triggers and linear two-point hedging rules, as shown in Fig. 2, are represented by one of the following equations:

If \( S_t + I_t < \text{Trigger}_1 \), then \( R_t = I_t + S_t \)

If \( \text{Trigger}_1 \leq S_t + I_t < \text{Trigger}_2 \), then \( R_t = Rs \) where \( Rs < D_t \)

If \( \text{Trigger}_2 \leq S_t + I_t < \text{Trigger}_3 \), then \( R_t = D_t \)

If \( \text{Trigger}_3 \leq S_t + I_t \) then \( R_t > D_t \)

where Trigger\(_i\) = specific value of \( S_t + I_t \) representing drought triggers \((i=1,2,3)\); and \( D_t \) = water demand during each time period \( t \). Drought triggers in a reservoir operating system depend on both hydrology of the system through prediction of forecast inflow \( (I_t) \), and economic benefits of operation, through evaluation of tradeoffs among immediate and future uses of water. Hedging rules converge to the well known standard operating policy (SOP) (as shown in Fig. 2) in the absence of enough knowledge of hydrologic or economic characteristics of a system (Klemes 1977). The problem in setting up a hedging rule for a water resources system is to calculate drought triggers (\( \text{Trigger}_n \)) as shown in Eq. (5).

Recently, Draper and Lund (2004) presented an analytical method for derivation of triggers in a hedging rule-based operating policy. They showed that a hedging rule is optimal when the economic marginal value of release and storage are equal

\[
\partial C(S)/\partial S = \partial B(R)/\partial R
\]

where \( B(R) \) = current water delivery benefits and \( C(S) \) represents expected value of future economic benefits from keeping water in the reservoir. Eq. (6) should be considered along with the water balance equation [Eq. (4)] as well as active and dead storage volume constraints. Draper and Lund (2004) solved this problem analytically for benefit and storage functions of different orders. They showed that in the case of quadratic benefit and storage value functions where \( B(R) = a_0 + b_0 R + c_0 R^2 \) and \( C(S) = a_s + b_s S + c_s S^2 \), the drought triggers are calculated as follows:

\[
\text{Trigger}_1 = (b_s - b_0)/(2c_s)
\]

\[
\text{Trigger}_2 = \text{Min}[D_t(1 + c_s/c_0) + (b_s - b_0))2c_s, \text{CAP}(1 + c_0/c_s) + (b_s - b_0))2c_s]
\]

and

\[
\text{Trigger}_3 = D_t + \text{Cap}
\]

Also, the optimum release, \( R^* \); in the condition when \( \text{Trigger}_1 \leq S_t + I_t < \text{Trigger}_2 \) [see Eq. (5)] will be

\[
R^* = \frac{\left[ b_s - b_0 + 2c_s(S_t + I_t)\right]}{[2(c_s + c_0)]}
\]

where \( D_t \) = water demand; \( \text{Cap} \) = maximum capacity of reservoir; and \( a_0, b_0, c_0, a_s, b_s, \) and \( c_s \) = constant values.
each time interval.

If the reservoir storage, 

the time operation of reservoirs, three factors control the optimum

optimal hedging rules. As shown in Eqs. (7)–(10), it may be easier to

directly for the optimal hedging rule, than to search directly for the

search for the optimal carryover storage value function, and then

these factors are available, optimal

shown in Fig. 2. Whenever the release benefit functions and the

optimal carryover storage value function are available, optimal

carryover storage value function are available, optimal

Fig. 2. Two-point reservoir operation hedging rule

The above equations give a two-point linear hedging rule as

as shown in Fig. 2. Whenever the release benefit functions and the

optimal carryover storage value function are available, optimal

hedging rules can be derived by Eqs. (7)–(10). It may be easier to

search for the optimal carryover storage value function, and then

derive the optimal hedging rule, than to search directly for the

optimal hedging rules. As shown in Eqs. (7)–(10), during a real

time operation of reservoirs, three factors control the optimum

releases that resulted from the hedging rules. These factors are

predicted available water, estimated water demand, and storage/

release benefit functions.

Value of Storage during Drought

If the reservoir storage, \( S_t \), is divided into some discrete levels at

each time interval \( t \), \( s_r \), then the value of water storage at the end

of each time interval is equal to the expected marginal value of

the additional release into the future, added from the sum of \( s_r \)

values, and assuming the optimal use of water in the future, dis-

counted at rate \( r \). According to Draper and Lund (2004) the eco-

nomics value of carryover storage, \( C(S) \), is defined as

\[
C(S) = \text{Max} \left[ \frac{EV}{T} \left( \sum_{r=1}^{n} B_t \left( R_{t} + s_r \right) \exp(-rt) \right) \right] 
\]

\[
- B_t(0) \exp(-rt) \right] 
\]

where \( B(R) = \text{release benefit function}; A = \text{available water in the}

present time period, which is the sum of water currently in the

reservoir plus the expected value of current period inflows to the

reservoir minus any water loss; \( \partial R / \partial A = \text{rate of release per unit of}

water availability}; \text{and exp}(-rt) = \text{discount factor. Regarding Eq.}

(11), the increased value of future release due exclusively to the

presence of carryover storage is expressed as the rate of release per

water available times the remaining carryover storage at each

future time

\[
\left( \frac{\partial R_t}{\partial A_t} \right) \left( S - \sum_{r=1}^{n} s_r \right) 
\]

The estimation of carryover value function is complex; and is

dependent on three factors:

- Release value \((B(R))\);
- Anticipated available water; and
- Reservoir capacity.

In this paper the following algorithm is used to calculate storage

value considering the above three factors:

1. Consider a streamflow trace. The expected streamflow trace

each real time operation is estimated by the K-NN estimation

model as described in the previous section;

2. Solve the following optimization model for the streamflow

trace and store the value of \( S_t \) as well as the maximized

value of \( B_t \):

\[
\text{Max} \sum_{r=1}^{T} B_t(R_t) 
\]

Subject to

\[
I_t + S_t - S_{t+1} - E_t = R_t 
\]

\[
0 < S_t < \text{CAP} 
\]

\[
S_1 = 0 
\]

where \( T = \text{time horizon when the reservoir reaches its maxi-

mum capacity.} \)

3. Consider \( S_1 = S_1 + \text{Cap}/n \) and resolve the optimization model

of Eq. (12).

4. Repeat step 3 by \( n \) times. In the last run of the model men-

tioned in step 2, \( S_1 \) is considered as the maximum capacity of

reservoir \( (\text{Cap}) \); and

5. \( n \) pairs of \((S_1, B_t)\) resulting by the resolving of Eq. (12) in step

2 define a discrete storage value function \( S \text{ versus } B_t \) assum-

ing the streamflow trace of step 1 as the anticipated long-

term hydrologic behavior of inflow into the reservoir.

To use the discrete function of \( C(S) \) in the hedging rule ex-

plained in “Hedging Rule,” the function should be approximated

by an analytical function (say quadratic function).

Case Study

The Zayandeh-rud River is the main surface water resource for

supplying irrigation demands in the central part of Iran, especially

the Isfahan metropolitan area. The Zayandeh-rud Reservoir con-

trols streamflow upstream of Isfahan city. The reservoir has a

volume of 1470 million \( m^3 \). Average annual inflow to the

Zayandeh-rud Reservoir is about 1,600 million \( m^3 \) including an

average annual flow of 600 million \( m^3 \) transferred from the adja-

cent Karoun River Basin. The Zayandeh-rud Basin (Fig. 3) has a

semiarid climate and it is sensitive to droughts.

The water year for management of the Zayandeh-rud Reser-

voir is from October to September. Two agricultural seasons are

considered in this basin: autumn and spring-summer. The first

season is from October to December with total water demand

equal to 294 10^6 \( m^3 \), and the second season is from April to Sep-

ember with total water demand equal to 756 10^6 \( m^3 \). At the end

of September, the regional water board of Isfahan (RWBI) de-

clares a firm agricultural water demand allocation in order to sign

contracts with water users/farmers. To avoid social and political

conflicts, this allocation should be realistic, and conservative

measures are not recommended due to the loss of income. So

RWBI needs a reliable approach in determining the water avail-

ability. If a drought occurs and an insufficient amount of water is

stored in the reservoir, the state of future water supply will be
critical. To conserve water and to minimize the impact of a severe drought in the future, the reservoir must be operated under certain restrictions.

There are some policies dictated by local and federal authorities which define the objectives of strategic operation of the Zayandeh-rud Reservoir. The priority of domestic and industrial water allocation is the highest among the water users, so allocation of these demands is mandatory in every situation as well as the allocation of minimum instream flow. The domestic and industrial water demand from October to March is 126 $10^6$ m$^3$ and it is equal to 324 $10^6$ m$^3$ from April to September.

Maximum benefit is obtained when all agricultural water demands are allocated. Based on the damages incurred during the recent droughts in the basin [Fig. 4(a)], the release value functions of the first and the second agricultural seasons are estimated, which are shown in Fig. 4(b). As it is shown in this figure, the release value functions are represented by quadratic functions of

$$B(R) = -0.00008R^2 + 0.0466R$$

and

$$B(R) = -0.0002R^2 + 0.2893R$$

for the first and the second agricultural seasons, respectively.

Thirty years of monthly inflow data to the Zayandeh-rud Reservoir for the period of 1972–2004 are used in this study. Two climate signals, El-Nino Southern Oscillation (ENSO) and North Atlantic Oscillation (NAO), which seem to be effective for predicting climate variations of the central and southern parts of Iran, are considered as potential predictors of Zayandeh-rud River streamflow. The southern oscillation index (SOI), an ENSO indicator, is considered as a predictor of Zayandeh-rud River streamflow. The Troup SOI, which is defined as the standardized difference of the sea level pressures at Tahiti minus Darwin multiplied by a factor of ten (Troup 1965) is used in this study. SOI from June to September and the total streamflow from June to September are used as the hydroclimatologic predictors of the streamflow for the first agricultural season. The NAO index is the difference between normalized sea level pressure over the Azores and Iceland. The usual index is given by the December to March difference between normalized sea level pressure over the Azores and Iceland. The Northern Atlantic Oscillation (NAO) is used in this study. Two

season’s streamflow (Araghinejad et al. 2006). The results of forecasting in 32 years of cross validation are shown in Fig. 5. The average volume error in percent during the first seasons is 23.0 while it is 12.3 during the second seasons. The average volume error of forecasting dry first seasons (seasons with less than average streamflow) is 24.1 while it is 15.1 during the dry second seasons.

**Modeling Approach**

Regarding the algorithm shown in Fig. 1, at the start of each agricultural season, inflow to the reservoir is predicted and decision on the amount of allocated water is made using the predicted available water, and the release and the carryover value functions of that season. Simulations are performed to explore the behavior of Zayandeh-rud water resources system using hedging rules and a well-known stochastic dynamic programming model, Bayesian stochastic dynamic programming (BSDP) developed by Karamouz and Vasiladis (1992). The recursive function of BSDP is as follows:

$$f_i(S_t, I_t, H_{t+1}) = \max\{B_i(S_t, I_t, R_t) + \alpha E_{i_t, i_{t+1}, \ldots, i_{t+T}}[f_{t+1}(S_{t+1}, I_{t+1}, H_{t+1})]\}$$

where $I+$inflow to the reservoir; $S=$reservoir storage; $R=$reservoir release; $H=$forecast inflow to the reservoir; $E=$expected value; $B=$operation benefit; and $\alpha=$discount factor.

Simulation of Zayandeh-rud reservoir operation is examined using the following two scenarios as:
1. Thirty-two years simulation of the system considering a perfect knowledge of future inflow. In this scenario, the reservoir is simulated considering the observed values of streamflow with the seasonal BSDP and hedging rules (HR) models. Furthermore, the performance of the BSDP in a monthly-basis operation is examined; and

2. Real-time optimization of the reservoir using long-lead streamflow forecasts. In this scenario, the use of long-lead forecasts of streamflow is examined through a real-time simulation of reservoir operation using the HR model. Moreover, the results of simulated operation are compared with those of actual operation of the reservoir during the recent drought in the basin.

**Performance Indicators**

Extreme drought occurred when the system is unable to supply any portion of agricultural water demands, while there will be no hydrological drought (normal condition) if the system can supply total agricultural water demands. Any case between these two conditions could be defined as mild to severe drought according to the portion of allocated agricultural water demands. In this study, two well-known characteristics of drought events, duration and severity, are used to examine the performance of the water resources system.

To define drought characteristics, first two variables are defined as the satisfactory, Sat, and unsatisfactory, U, values in providing a prespecified demand from a water resources system

\[
\text{If } R_i \geq D_i \text{ then } R_i \in \text{Sat} \text{ and } Z_t = 0
\]

\[
\text{else } R_i \in \text{U} \text{ and } Z_t = 1
\]

Then the duration and severity of droughts are defined as

\[
\text{Severity} = \sum U
\]

\[
\text{Duration} = \sum Z_t
\]

Drought duration gives an indication of how slow the recovery will be once the system experiences a failure. Severity is a measure of the magnitude of failure in the water supply system.

**Table 1. Performance Indices Using Monthly and Seasonal BSDP as well as Hedging Rules**

<table>
<thead>
<tr>
<th>Model</th>
<th>Drought event (number)</th>
<th>Time period (year)</th>
<th>Duration (agricultural season)</th>
<th>Severity (10^6 m^3)</th>
<th>Loss (million US dollars)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2</td>
<td>1981–1986</td>
<td>8</td>
<td>1,128</td>
<td>30.05</td>
</tr>
<tr>
<td></td>
<td>4</td>
<td>1997–2002</td>
<td>11</td>
<td>2,874</td>
<td>1,583.19</td>
</tr>
<tr>
<td></td>
<td>Summation</td>
<td></td>
<td>26</td>
<td>4,973</td>
<td>220.54</td>
</tr>
<tr>
<td>Seasonal BSDP</td>
<td>1</td>
<td>1981–1986</td>
<td>7</td>
<td>772</td>
<td>24.74</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>1989–1991</td>
<td>4</td>
<td>439</td>
<td>16.00</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1994–2002</td>
<td>11</td>
<td>2,424</td>
<td>101.25</td>
</tr>
<tr>
<td></td>
<td>Summation</td>
<td></td>
<td>22</td>
<td>3,634</td>
<td>141.99</td>
</tr>
<tr>
<td>Hedging rule</td>
<td>1</td>
<td>1982–1986</td>
<td>4</td>
<td>551</td>
<td>12.88</td>
</tr>
<tr>
<td></td>
<td>3</td>
<td>1998–2002</td>
<td>10</td>
<td>2,240</td>
<td>7.58</td>
</tr>
<tr>
<td></td>
<td>Summation</td>
<td></td>
<td>17</td>
<td>2,919</td>
<td>31.58</td>
</tr>
</tbody>
</table>
Moreover the drought loss due to the shortage in agricultural demand allocation and reliability of agricultural water demands are used as other indicators of the models performance. The reliability is defined as the percent of operation time that a certain percent of agricultural demand is allocated. On the other hand, the reliability of allocating $\beta$ percent of agricultural water demand at each agricultural season is calculated as the number of agricultural seasons when at least $\beta$ percent of demand is allocated, over the number of all agricultural seasons considered in a simulation scenario. The best operating policy is the one that minimizes the drought duration, severity, and loss, and maximizes the reliability.

**Results and Discussion**

The results of the first scenario are shown in Tables 1 and 2. Table 1 shows the drought duration and severity resulted by applying monthly and seasonal BSDP as well as hedging rules, considering perfect knowledge of forecasts for 32 years (64 agricultural seasons) of simulation of Zayandeh-rud reservoir operation. Table 2 shows the reliability of irrigation demand allocation obtained by hedging rules and seasonal BSDP.

As shown in Table 1, using BSDP in monthly time steps, four drought events are observed and 26 out of 64 agricultural seasons are affected by drought. The system experiences a total of 4,973 $10^{16}$ m$^3$ shortage during 32 years of operation. Drought damage is estimated as $220$ million. Using BSDP in seasonal time steps, drought events have reduced to three events with a total of 22 agricultural seasons duration and 3,634 $10^{16}$ m$^3$ severity. In this case, the drought loss is reduced to $142$ million. The reduction in drought severity is observed in all drought periods of the basin. The results demonstrate that seasonal operation of the reservoir using long-lead forecasts with the BSDP model could reduce the drought damage by 45% in comparison with the results presented in Table 2. As shown in Table 3, four drought events with a total of 23 seasons duration and 3,912 $10^{16}$ m$^3$ shortage is observed. The operation resulted in about $123$ million damage. The results of Table 3 show a decrease in the performance operation of the reservoir compared to the results of Table 1 as they show more drought duration, more drought severity, and more estimated drought loss. The reason for this is attributed to the error of long-lead streamflow forecasting in real time reservoir operation. However, even in this case, the performance of the reservoir is better than the case of using BSDP with perfect forecasts. Considering the results of HR shown in Table 2 as the baseline, the results of real time operation using the forecast model has increased the drought severity and damage by 34 and 292%, respectively.

Fig. 6 shows the variation of actual reservoir storage and simulated reservoir storage using the HR model in real time operation of the reservoir during the period of 1995–2003, when the system had experienced a record drought. The model uses the same constraints that existed in the real world operation of the reservoir. The performance of HR has reduced the recent drought damage by 80%, to $9.68$ million. HR results presented in Fig. 6 do not consider the short-term operation of the reservoir so this reduction is not expected in a real world operation; however it is emphasized that use of the proposed approach could significantly reduce the drought damages.

**Summary and Conclusions**

An algorithm has been proposed to operate the Zayandeh-rud Reservoir in a strategic time frame. The approach determines the volumes of storage plus predicted inflow to trigger several phases of rationing under the objective of minimizing drought damages.

### Table 2. Reliability of Agricultural Demand Allocation Using Seasonal BSDP and Hedging Rules

<table>
<thead>
<tr>
<th>Model</th>
<th>100%</th>
<th>90%</th>
<th>70%</th>
<th>50%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hedging rules</td>
<td>59</td>
<td>59</td>
<td>90</td>
<td>98</td>
</tr>
<tr>
<td>BSDP</td>
<td>72</td>
<td>75</td>
<td>84</td>
<td>91</td>
</tr>
</tbody>
</table>

### Table 3. Performance Indices Using Hedging Rules with Real Time Forecasts

<table>
<thead>
<tr>
<th>Drought event (number)</th>
<th>Time period (year)</th>
<th>Duration (agricultural season)</th>
<th>Severity ($10^6$ m$^3$)</th>
<th>Loss (million United States dollars)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1971–1975</td>
<td>4</td>
<td>245</td>
<td>1.49</td>
</tr>
<tr>
<td>2</td>
<td>1982–1986</td>
<td>6</td>
<td>901</td>
<td>15.63</td>
</tr>
<tr>
<td>4</td>
<td>1998–2002</td>
<td>8</td>
<td>1,885</td>
<td>89.92</td>
</tr>
<tr>
<td>Summation</td>
<td></td>
<td>23</td>
<td>3,912</td>
<td>123.8</td>
</tr>
</tbody>
</table>

The approach is designed to provide guidance to the water managers by determining the restriction that should be considered in long-term operation of the reservoir.

The approach uses long-lead forecasts as well as hedging rules to activate specific restrictions on agricultural demand allocation during and when anticipating a drought. This approach is suitable for considering the climatic information in the reservoir operation. The major contribution of the proposed algorithm is to integrate various components such as inflow forecasts, release value function, and reservoir characteristics to provide a reliable decision tool. Results indicate that operating schedules from the proposed approach, which consider the aspect of drought mitigation, are significantly different from those obtained by a model that does not consider this issue. In the simulation scenarios, comparing the proposed approach with the actual operation of the Zayandeh-rud Reservoir, the effectiveness of the approach was demonstrated by decreased drought damage by a factor of 80%.

From the standpoint of water resources decision making, the proposed approach has a potential to incorporate the hydroclimatological state of the basin into water resources related decisions. This is especially valuable when there is a strong relationship between predictors and climate variability in a basin. The proposed approach can be easily improved to also incorporate short-term operation. Depending on the long-term decision, it is possible to use short-term tactics to decide on optimal water release and conservation schemes in real time operation. This approach can be also generalized to a wider class of reservoir management problems such as multipurpose multireservoir systems with variable water demands.

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References


