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Reservoir Operation Rules with Uncertainties in Reservoir Inflow and Agricultural Demand Derived with Stochastic Dynamic Programming

Shima Soleimani[1]; Omid Bozorg-Haddad[2]; and Hugo A. Loáiciga, F.ASCE[3]

Abstract: A proposed stochastic dynamic programming (SDP) method with uncertainties in stream flow and water demand is developed to calculate optimal reservoir operation rules. The SDP method extends the classic SDP method that considers only one uncertainty in its operation rules. Time series of reservoir inflow and agricultural water demand for the Aydoghmoush Reservoir in eastern Azarbayejan, Iran, were obtained from meteorological data, available climate parameters, hydrologic data, and crop water demand. The application of the developed SDP with two uncertainties was evaluated with operation rules corresponding to four different scenarios, and optimal reservoir releases were determined for a drought year. Reservoir operation results were evaluated with different performance indices. This study's results demonstrate the advantage of considering uncertainties in reservoir inflow and water demand with the SDP method. The developed SDP method has general applicability under a range of climatic conditions, and the calculated operation rules cover the expected ranges of streamflow and water demand during the operating years. **DOI:** 10.1061/(ASCE)IR.1943-4774.0001065.
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Author keywords: Optimal operation rules; Stochastic dynamic programming; Reservoir inflow; Water demand.

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Introduction

The simultaneous consideration of uncertainties in numerous aspects of water resources systems are commonly neglected, as exemplified by various studies, such as reservoir operation (Ahmadi et al. 2014; Bolouri-Yazdeli et al. 2014), groundwater resources (Bozorg-Haddad et al. 2013; Fallah-Mehdipour et al. 2013b), conjunctive use operation (Fallah-Mehdipour et al. 2013a), design operation of pumped-storage and hydropower systems (Bozorg-Haddad et al. 2014), flood management (Bozorg-Haddad et al. 2015b), water project management (Orouji et al. 2014), qualitative management of water resources systems, (Orouji et al. 2013; Bozorg-Haddad et al. 2015a; Shokri et al. 2014), water distribution systems (Seifollahi-Aghmiuni et al. 2013; Soltanjalili et al. 2013; Beygi et al. 2014), and algorithmic developments (Ashofteh et al. 2015b).

Reservoir operation involves variables that are affected by uncertainty. That uncertainty stems from multiple sources, such as future water demands and reservoir inflows. One must take uncertainty into account to calculate appropriate reservoir operation. Replacing uncertain variables with their expected values or their worst estimates can have severe influence on the performance assessment of water resource systems (Loucks et al. 1981). The stochastic dynamic programming (SDP) method derived from dynamic programming (DP) is suitable to tackle reservoir operation problems that take uncertainty into account (Yakowitz 1982; Stedinger et al. 1984). The SDP method has been applied in various works to calculate reservoir operation policies (Lubow 1994; Ben Alaya et al. 2003; Mousavi et al. 2004; Cervellera et al. 2006; Raje and Mujumdar 2010).

Stochastic models use statistical descriptions of reservoir streamflow and forecast processes instead of applying a specific streamflow sequence (as do deterministic models) to determine operating policies. Several authors applied sampling stochastic dynamic programming (SSDP) that generates operating policies capturing the temporal and spatial characteristics of reservoir inflows (Bras et al. 1983; Stedinger et al. 1985; Kelman et al. 1990). Shokri et al. (2013) pioneered the use of the SDP method considering the uncertainty in streamflow and sediment inflows to obtain optimal operating policies for water supply and sediment flushing.

A few authors have considered water demand uncertainty in modeling studies (Milliken and Taylor 1981). Maddock (1974) developed a quadratic programming model in which supply and demand resources were treated stochastically. Vasiliadis and Karamouz (1994) developed a demand-driven stochastic dynamic programming (DDSP) in which reservoir inflow's uncertainty was accounted for and monthly water demand varied within a year (that is, intraannually variable), but the water demand was set constant in each month interannually. The application of the model proved beneficial using monthly inflows of the Gunpowder River, located in the United States, for a 95-year long time series.

Agricultural water demands have noticeable intraannual variations, and these variations can influence the supply potential of municipal and industrial water use, and, thus, reservoir operation rules in general. Variations in climate, economic and social conditions, water and soils resources, and cropping patterns are important factors determining agricultural water demand. In fact, agricultural water demand exhibits remarkable monthly variations

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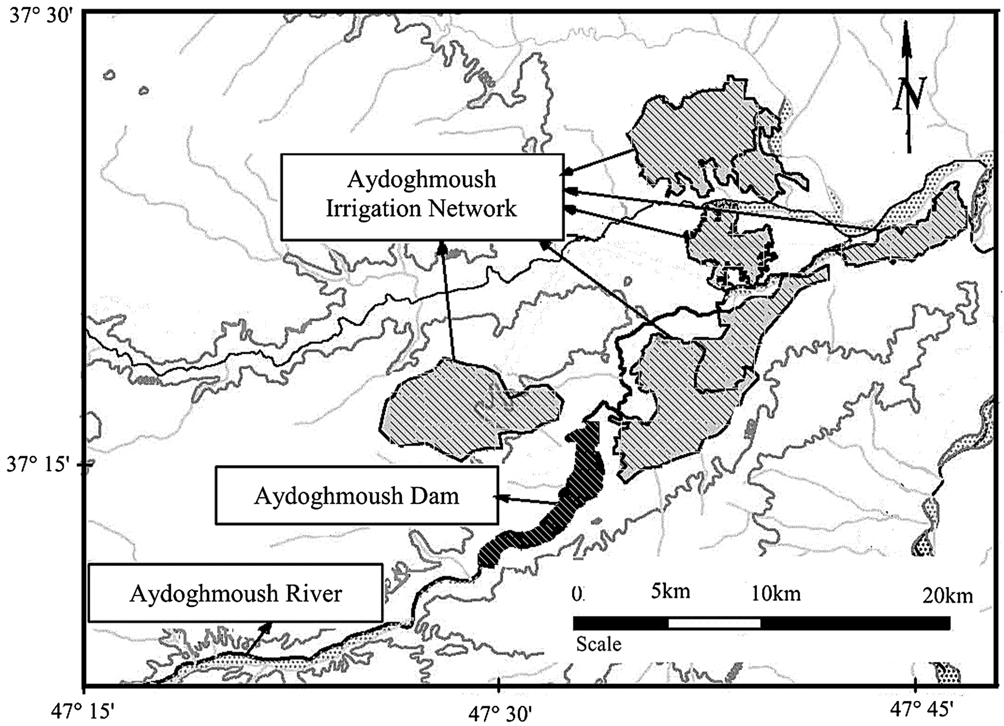

Fig. 1. Location of the case study (data from Ashofteh 2015)

within a year, which poses challenges to the optimization of reservoir operation rules. This paper presents a SDP method that considers the stochastic nature of reservoir inflows and the variability of agricultural water demands. The results demonstrate the advantages of introducing these two uncertainties in the development of optimal reservoir operation rules.

Methodology

This paper's methodology comprises five sections: (1) case study, (2) calculation of the total water demand, (3) description of the reservoir operation model, (4) evaluation and definition of the SDP method, and (5) definition of the optimization scenarios.

Case Study

The Aydoghmoush River is located in the Ghezelozan Basin in East Azarbayejan, Iran. Its catchment area equals $1,800\ \mathrm{km}^2$. The Aydoghmoush dam regulates river flow to meet downstream irrigation water use. The irrigation network area is approximately 13,500 ha, located in the southern and southeastern Mianeh, Iran, between 47° 33′ and 49° 37′ longitude, and 37° 16′ and 37° 31′ latitude (Ashofteh et al. 2013a). Fig. 1 shows the location of the study area.

A 14-year time series of reservoir inflow (1987–2000) was used in this paper (Ashofteh et al. 2013b). The monthly water demand of each crop was calculated for every year of the time series. The same months of different years had distinct water demands. The monthly water demand was determined by applying meteorological data and other required information, such as the farming calendar, cultivation area, and cropping pattern from 1987 through 2000 (Ashofteh et al. 2014).

Meteorological data from 1987 through 2000 were obtained from the Mianeh synoptic station located downstream of the Aydoghmoush dam. Hydrometric data were gained from the

Table 1. Irrigation Area of Each Crop in the Aydoghmoush Irrigation Network

Crop	Area under irrigation (ha)
Walnut orchards	4,725
Wheat	1,620
Potato	1,620
Alfalfa	1,620
Barely	1,080
Soybean	1,080
Feed corn	1,080
Forage	675

Motorkhne hydrometer station located near the Mianeh station. The major crops are walnut orchards, wheat, potato, alfalfa, barely, soybean, feed corn, and forage (Ashofteh et al. 2015a). Table 1 lists irrigation data and Table 2 presents the farming calendar.

The monthly time series of inflow and agricultural water demand exhibited pronounced variability. Fig. 2 shows inflow and water demand in the month of April from 1987 through 2000. Fig. 3 depicts the variability of annual reservoir inflow and water demand from 1987 through 2000. Fig. 2 shows that the average and standard deviation for inflow were 42.20 and 20.62 ($10^6\ \mathrm{m}^3$), respectively, and for agricultural water demand it was 3.54 and 1.93 ($10^6\ \mathrm{m}^3$), respectively, in the month of April. According to Fig. 3 the average and standard deviation for annual reservoir inflow was 152.79 and 80.94 ($10^6\ \mathrm{m}^3$), respectively, and for annual agricultural water demand it was 143.58 and 12.53 ($10^6\ \mathrm{m}^3$), respectively.

Figs. 2 and 3 indicate that reservoir operation must consider the uncertainty in reservoir inflow and agricultural water demand. There most likely are substantial differences between the expected performance of the system and its actual value because of the variability of reservoir inflow and agricultural water demand. This paper calculated reservoir operation rules that simultaneously

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Table 2. Temporal Cropping Pattern in the Aydoghmoush Irrigation Network

Crop	Month											
	January	February	March	April	May	June	July	August	September	October	November	December
Walnut orchard	a	a	a	—	—	—	—	—	—	—	a	a
Wheat	—	—	—	—	—	—	a	a	a	—	—	—
Potato	a	a	a	a	—	—	—	—	—	—	a	a
Alfalfa	a	a	a	a	—	—	—	—	—	—	a	a
Barely	—	—	—	—	—	—	a	a	a		—	—
Soybean	a	a	a	a	—	—	—	—	—	a	a	a
Feed corn	a	a	a	a	—	—	—	—	—		a	a
Forage	a	a	a	a	—	—	—	—	—	a	a	a

[a]Illustrates the defined crop is cultivated in the defined month.

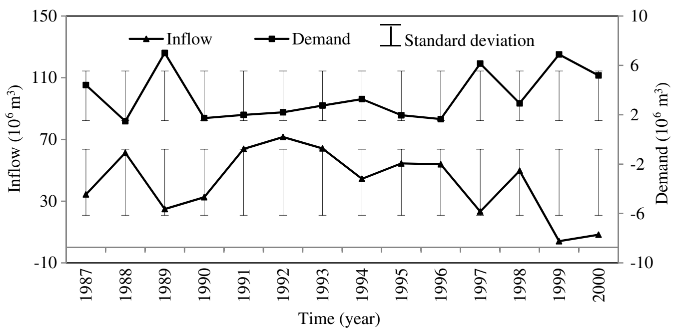

Fig. 2. Variability of monthly inflow and water demand in April from 1987 to 2000

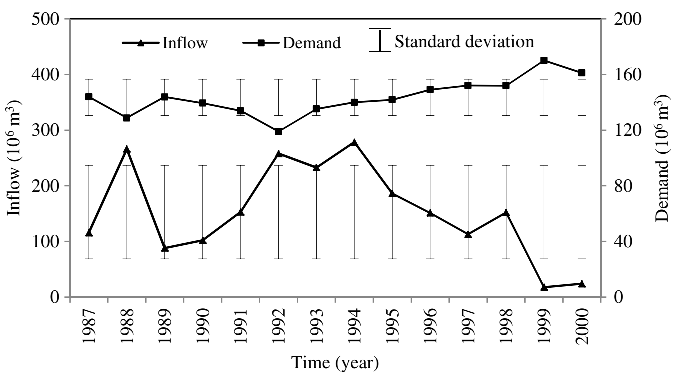

Fig. 3. Variability of annual inflow and water demand from 1987 to 2000

involved inflow and water demand uncertainties using the SDP method.

Calculation of the Total Agricultural Water Demand

This section describes the calculation of crop evapotranspiration, effective precipitation, net irrigation requirement, and downstream agricultural water demands.

Crop Evapotranspiration

Crop evapotranspiration is calculated using the FAO-24 method (Doorenbos and Pruitt 1984). The method is summarized by Eq. (1)

$$ET_{C_{t,y}} = K_{C_{t,y}} \times ET_{0_t} \quad (1)$$

where $ET_{C_{t,y}}$ = evapotranspiration of crop y in month t; $K_{C_{t,y}}$ = coefficient of crop y in month t; and ET_{0_t} = potential crop evapotranspiration in month t. The potential evapotranspiration is calculated with the FAO Penman-Monteith method (Ashofteh et al. 2014).

Effective Precipitation

The part of precipitation that supplies a portion of a crop's water demand is called effective precipitation. It is dependent on the meteorology of the case study region (Ashofteh et al. 2014). This work calculates the effective precipitation using the Soil Conservation Service (SCS) method embedded in the CROPWAT software (Smith 1992). Eqs. (2) and (3) describe the relation between precipitation and effective precipitation

$$P_{\mathrm{eff}_t} = P_t/125 \times (125 - 0.2P_t) \qquad 0 < P_t \leq 250\ \mathrm{mm} \quad (2)$$

$$P_{\mathrm{eff}_t} = 125 + 0.1P_t \qquad P_t > 250\ \mathrm{mm} \quad (3)$$

where P_{eff_t} and P = average effective precipitation (mm) and average precipitation (mm) in month t, respectively.

Net Irrigation Requirement

The net water requirement equals the difference between crop evapotranspiration ($ET_{C_{t,y}}$) and effective precipitation (P_{eff_t}) in month t

$$\mathrm{NIR}_{t,y} = ET_{C_{t,y}} - P_{\mathrm{eff}_t} \quad (4)$$

if $ET_{Ci,y} >= P_{\mathrm{eff}}$, and $\mathrm{NRI}_{t,y} = 0$ if $P_{\mathrm{eff}} > ET_{Ci,y}$, in which $\mathrm{NIR}_{t,y}$ = net water requirement (mm) of crop y in month t.

Downstream Agricultural Water Demand

The volume of the monthly agricultural water demand is calculated by multiplying the net water requirement of each crop by its planted acreage and adding up all the crops' net water requirements. Irrigation losses were neglected in this work.

Reservoir Operation Model (Simulation)

The developed SDP method with two uncertainties treats reservoir storage at the beginning of each period, reservoir inflow during each period, and water demand in each period as state variables. The reservoir releases during each period or the reservoir storage at the end of each period are the decision variables. Because of discretization of the SDP solution space, it is necessary to divide storage volume, reservoir inflow, and water demand into NK, NI, and NM classes, such that NK, NI, and NM are the total number of

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the storage volume, reservoir inflow, and water demand classes, respectively. The basic equations for reservoir operation are (Loucks et al. 1981)

$$S_{1,t+1} = S_{kt} + Q_{it} - EV_{\mathrm{kimlt}} - R_{\mathrm{kimlt}} - SP_{\mathrm{klt}} \tag{5}$$

$$SP_{kt} = \begin{cases} S\max - S_{1,t+1} & \text{if } S\max \geq S_{1,t+1} \\ 0 & \text{if } S\max < S_{1,t+1} \end{cases} \tag{6}$$

$$S\max \leq S_t \leq S\min \tag{7}$$

$$0 \leq R_{\mathrm{kimlt}} \leq De_{mt} \tag{8}$$

where k = class index of reservoir storage volume at the beginning of each period ($k = 1, 2, \ldots, NK$); i = class index of reservoir inflow volume ($i = 1,2, \ldots, NI$); m = class index of water demand volume ($m = 1,2, \ldots, NM$); l = class index of reservoir storage volume at the end of each period ($l = 1,2, \ldots, NK$); $S_{l,t+1}$ = storage volume in the l-th class in the $(t+1)$-th period; S_{kt} = storage volume in the k-th class in the t-th period; Q_{it} = inflow volume in the i-th class in the t-th period; EV_{kimlt} = reservoir loss volume in the k-th, i-th, m-th, and l-th class in the t-th period; R_{kimlt} = reservoir release in the k-th, i-th, m-th, and l-th class in the t-th period; SP_{klt} = reservoir spillage in the k-th and l-th class in the t-th period; Smax = maximum reservoir storage; Smin = minimum reservoir storage; and De_{mt} = water demand in the m-th class in the t-th period.

Evaluation and Definition of the SDP Method with Uncertainties

The reservoir system reliability, resiliency, and the objective function expressed as the sum of square deficits for the supply of agricultural water demand with reservoir releases are defined in the subsequent sections.

Reliability

The reliability index has two expressions, namely, volumetric reliability [Eq. (9)] and time-based reliability [Eq. (11)]. A successful period is a period in which the amount of reservoir release meets a specified threshold of agricultural water demand. The threshold can be equal to or less than 100% (McMahon et al. 2006)

$$RV = 1 - \frac{\sum_{t=1}^{N}(Def_t)}{\sum_{t=1}^{N} De_t} \tag{9}$$

$$Def_t = \begin{cases} De_t - R_t & De_t > R_t \\ 0 & De_t \leq R_t \end{cases} \tag{10}$$

$$RT_{\alpha\%} = \frac{NS_{\alpha\%}}{N} \tag{11}$$

where RV = volumetric reliability index; De_t = water demand in the t-th period; R_t = reservoir release in the t-th period; $RT_{\alpha\%}$ = time-based reliability index for a demand threshold equal to $\alpha\%$; $NS_{\alpha\%}$ = number of successful intervals (an interval is made up of consecutive success periods); and N = total number of reservoir operation periods.

Resiliency

The resiliency index measures how fast a reservoir exits from a failure condition as described by Eq. (12) (Matalas and Fiering 1977)

$$\varphi_{\beta\%} = \frac{fs}{fd} \tag{12}$$

where $\varphi_{\beta\%}$ = resiliency index for a $\beta\%$ threshold; fs = number of sequential failure time intervals; and fd = number of failure periods.

Objective Function

The objective is to minimize the sum of square deviations between reservoir releases and downstream water demand as written in Eqs. (13) and (14)

$$\mathrm{Min} f = \sum_{t=1}^{N} B_t \tag{13}$$

$$\begin{matrix} 0 \leq R_t \leq De_t \\ R_t > De_t \\ R_t < 0 \end{matrix} \qquad B_t = \begin{cases} (R_t - De_t)^2 \\ 0 \\ 10^{10} \end{cases} \tag{14}$$

where B_t = objective function for the t-th period; and f = objective function for the total interval of operation.

The classic SDP method considers the uncertainty of reservoir inflow. Yet, water demand uncertainty also has an important role in the calculation of reservoir operating rules. This work includes the uncertainty in water demand as a second source of uncertainty in the proposed SDP method.

Classification

The reservoir storage volume and the uncertain variables (reservoir inflow and agricultural water demand) were discretized on the basis of the SDP method. The reservoir's active storage volume was discretized into different classes (Karamouz and Vasiliadis 1992). This research discretized the storage volume, reservoir inflow, and water demand by means of the equal-length method (Maimon and Rokach 2005). In this method the value of the difference between the minimum and the maximum data values is classified into classes with equal and fixed length, and each class frequency is determined by counting the number of data that fall between the upper and the lower boundary of each class.

Uncertainty in SDP

The Markov chain was applied in this work to deal with uncertain variables (Hastings 1970). The relation between future and previous values of a Markov chain, $X(t)$, depends only on the value of the chain at the current time (Papoulis 1984)

$$F_x(X_{t+k}|X_t, X_{t-1}, \ldots) = F_X(X_{t+k}|X_t) \tag{15}$$

where X_t = Markov chain value in the t-th period; and $F_X(a|b)$ = probability of a in period $t+k$ if b occurs in period t. According to the Markov chain, the occurrence probability of every inflow class in the $(t+1)$-th period depends only on inflow volume in the t-th period. The transition probability is calculated using historical data [Eq. (16)]

$$TP(i,j,t) = P[\mathrm{Scenario}(j, t+1)|\mathrm{Scenario}(i,t)] \tag{16}$$

where TP = transition probability matrix, showing the probability that inflow be in the j-th class in the $(t+1)$-th period given that the

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inflow in the t-th period is in the i-th class; Scenario $(j,\ t+1)$ = occurrence of inflow in the j-th class and $(t+1)$-th period; and Scenario (i, t) = occurrence of i-th class in the $t-h$ period.

In problems that involve two uncertainties, it is necessary to determine the probability of the inflow volume and water demand in each period. The Markov chain for two uncertainties is given by Eq. (17) (Shokri et al. 2013)

$$F_{X,Y}[(X,Y)_{t+k}|(X,Y)_t,(X,Y)_{t-1},\ldots]=F_{X,Y}[(X,Y)_{t+k}|(X,Y)_t] \tag{17}$$

where $(X,Y)_t$ = values of the variables X and Y in the t-th period; and $F_{X,Y}[(b,c)|(d,e)]$ = probability of occurrence of $(b,\ c)$ given that $(d,\ e)$ has occurred.

Eq. (18) is obtained from Eq. (17) as follows (Shokri et al. 2013)

$$TP'(i,m,j,n,t)=P[\text{Scenario}(j,n,t+1)|\text{Scenario}(i,m,t)] \tag{18}$$

where TP' = transition probability matrix, showing simultaneously the occurrence probability of inflow and water demand in j-th and n-th classes in the $(t+1)$-th period, subject to inflow and water demand in the t-th period is in the i-th and m-th classes; Scenario $(j,\ n,\ t+1)$ = occurrence of inflow and water demand in the j-th and n-th classes in the $(t+1)$-th period; and Scenario $(i,\ m,\ t)$ = occurrence of inflow and water demand in the i-th and m-th classes in the t-th period.

SDP Method with Backward Recursion for Reservoir Operation Problem with Two Uncertainties

The backward-recursion SDP algorithm with two uncertainties is similar to the classic SDP algorithm by starting the simulation at the most recent simulation period. For each state of the reservoir storage volume, inflow volume, and water demand volume, the optimal reservoir release volume and objective function are calculated. The SDP algorithm moves backward to the calculation step $t-1$, and the optimal reservoir release volume and objective function in each class of the reservoir storage volume, inflow volume, and water demand volume are determined using Eq. (19)

$$f_t^z(k,i,m)=\left[\text{Min}B_{\text{kimlt}}+\sum_{j=1}^{NI}\sum_{n=1}^{NM}TP'(i,m,j,n,t).f_{t+1}^{z-1}(l,j,n)\right] \tag{19}$$

where B_{kimlt} = value of the objective function in the t-th period when storage volume at the beginning of the period, inflow, water demand, and storage volume at the end of the period are in the k-th, i-th, m-th, and l-th classes, respectively; $f_t^z(k,i,m)$ = objective function value at the z-th calculation step; and z = calculation step counter.

The SDP algorithm starts searching the best solution for each interval starting with the most recent period and proceeds backward in time to the first simulation period. After that it returns to the most recent interval. The recursions from the most recent interval to the first interval, and from the first interval to the most recent interval, continue until the reservoir storage in two consecutive calculation steps for each interval become equal. This is the chosen convergence criterion applied in this paper. Fig. 4 portrays the SDP method with two uncertainties.

Definition of the Optimization Scenarios

This work considered four different scenarios in which each scenario had a reservoir operating rule quantifying the effect of the either one or both uncertain variables on reservoir water releases. The objective function and performance indices were determined under four scenarios applied to a drought year with the purpose of evaluating the performance of the SDP method. The four optimization scenarios are as follows:

- Scenario 1: calculation of the optimal reservoir operation policy using the proposed SDP method that considers inflow and water demand uncertainties;
- Scenario 2: calculation of the optimal reservoir operation policy using the classic SDP method that considers inflow uncertainty only;
- Scenario 3: calculation of the optimal reservoir operation policy using the classic SDP method that considers water demand uncertainty only; and
- Scenario 4: calculation of the optimal reservoir operation policy with nonlinear programming using the *Lingo 11.0* software considering known inflow and water demand.

Results and Discussion

The reservoir inflow and water demand volume were classified into 20 classes (Vasiliadis and Karamouz 1994). The transition probability matrices of inflow and water demand were calculated. To illustrate more clearly, these authors discretized the reservoir storage volume, inflow, and water demand volume into two classes to show a sample of transition probability instead of the real one. A monthly time step was chosen in this study. According to Table 3, for example, if both inflow and agricultural water demand are in class 1 in April, there is 12.2% chance that the inflow class and water demand class are in classes 1 and 2 in May, respectively.

The next step was the calculation of the objective function for all permutations of reservoir storage volume at the beginning and the end of each period, inflow volume in each period, and water demand volume in each period. Reservoir release was obtained from the reservoir storage at the beginning and the end of each period, inflow volume in each period, and reservoir loss volume according to Eq. (5). A large penalty in the objective function was excised in periods that have negative releases. Repeated iterations of the SDP method produced convergence to the optimal release volumes in each period.

The operation rule curve for a sample month (October) for the inflow classes and when water demand is in the 1, 5, 10, 15, and 20 classes is shown in Fig. 5. Fig. 5 shows that for all water demand classes, the operation curves had logical trends, such that whenever the number of storage, inflow, and demand volume classes increased, water release volume also increased. This is evidence that the discretization scheme used was appropriate. Fig. 5 indicates that the optimal water release was obtained for every combination of inflow and agricultural water demand values by applying the rule curve of reservoir operation for each month, and all 20 classes of inflow and water demand.

The reservoir operating policies for the first three scenarios were calculated, and the optimal reservoir releases corresponding to the four optimization scenarios in a drought year were calculated. This allowed the assessment of the role of the uncertainties in inflow and water demand on the rule curves of reservoir operation. Moreover, optimal operation rules for Scenario 4 allowed comparison with the optimal operation rules obtained considering uncertainties per Scenarios 1, 2, and 3. It was clarified that the initial and terminal storage volume during a drought year were made equal to each other according to the carry-over rule. In this manner the initial storage volume was placed in its first class.

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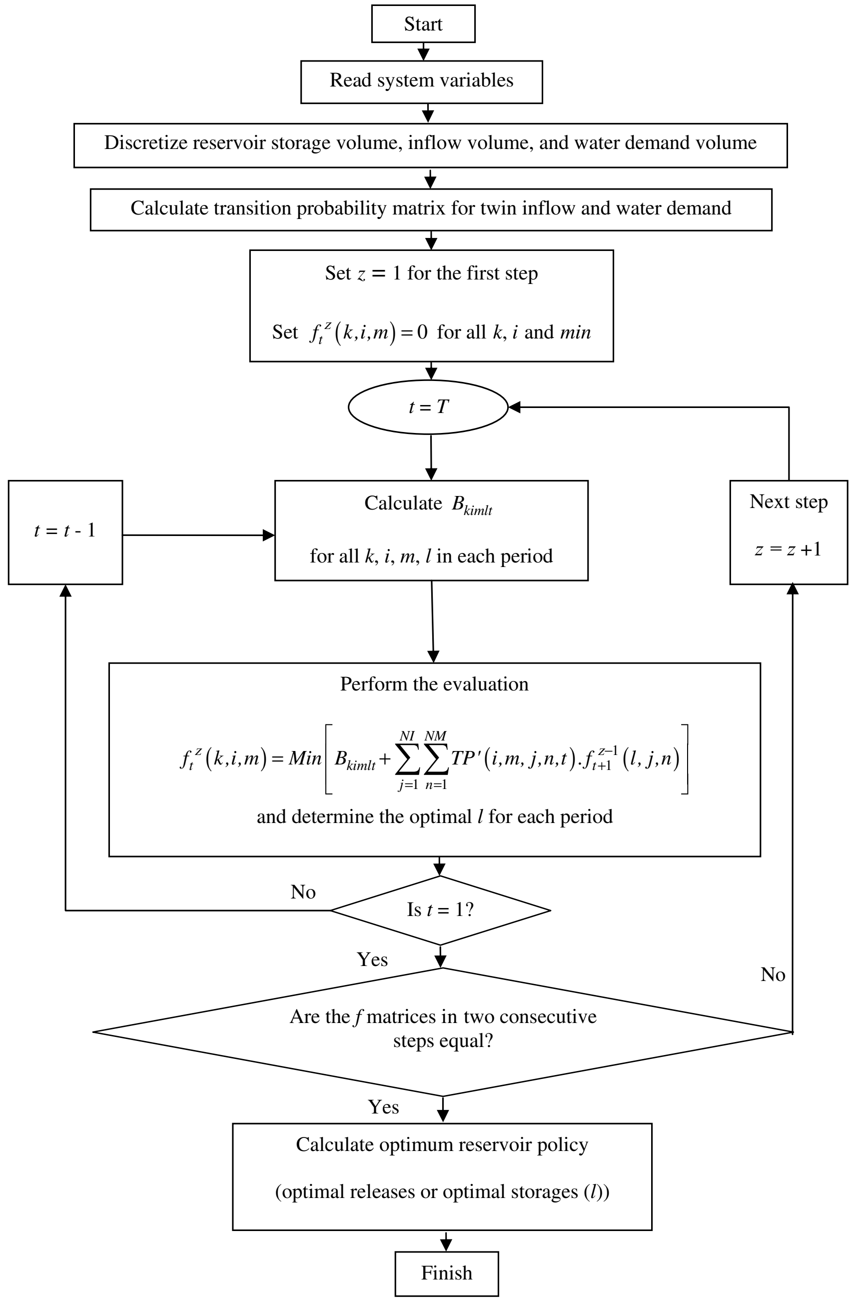

Fig. 4. Flowchart of the SDP with two uncertainties

Table 3. Example of Transition Probabilities April-May Considering Uncertainty of Inflow and Water Demand

Inflow class in May			
1	1	2	2
	Water demand class in May		
1	2	1	2
	Inflow class in April		
1	1	2	2
	Water demand class in April		
1	1	2	2
0.735	0.122	0.122	0.020
0.122	0.735	0.020	0.122
0	0	0	0
0	0	0	0

Fig. 6 depicts the inflow volumes and water demand volumes of a drought year. The average of the reservoir inflow and agricultural water demand equaled 2.00 and 13.34 (10^6 m^3), respectively.

The optimal operation rule curve on the basis of the classic SDP method under Scenario 2 for a sample month (October) is depicted in Fig. 7. Fig. 7 shows that agricultural water demand had no influence on the rule curve behavior. According to Fig. 7, agricultural water demand was approximately 6.5 (10^6 m^3) and was placed in the 4th class of agricultural water demand in October. The shape of the rule curve had more similarity to Fig. 5(b), in which agricultural water demand was in its 5th class.

The optimal operation rule curve for a sample month (October) on the basis of Scenario 3 is presented in Fig. 8. Recalling from Fig. 6, the inflow value for October was 1 (10^6 m^3), which was placed in its second class. According to Fig. 8, reservoir release

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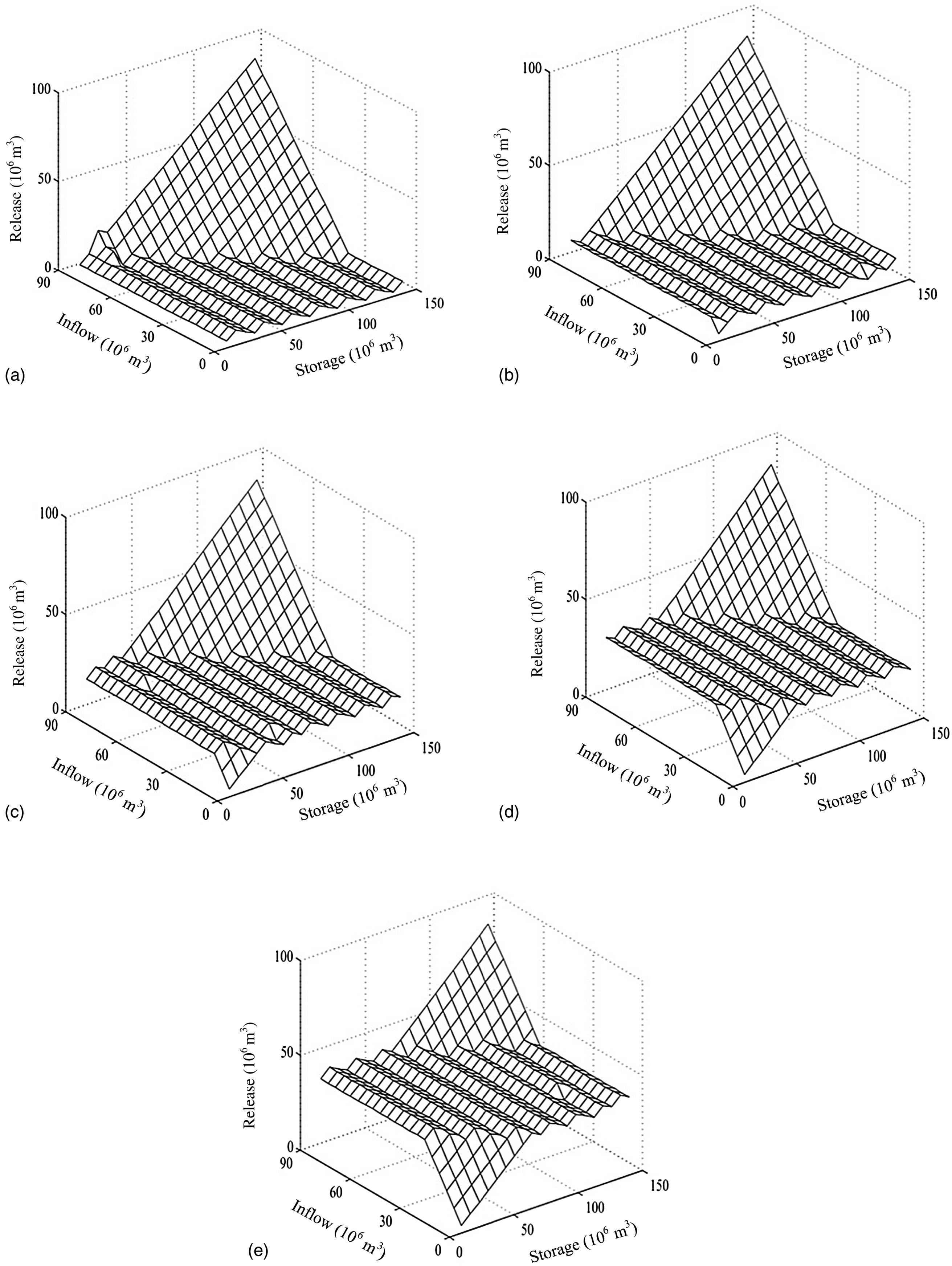

Fig. 5. Optimal operation rule curves for October for all inflow classes when water demand is in the (a) 1; (b) 5; (c) 10; (d) 15; (e) 20 class

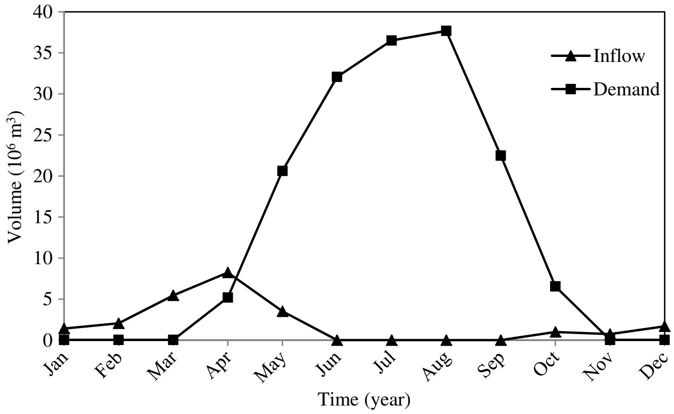

Fig. 6. Inflow volume and water demand volume for a drought year

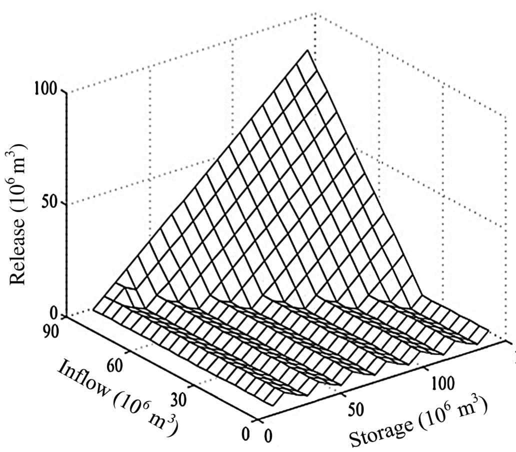

Fig. 7. Optimal operation rule curve for October on the basis of Scenario 2

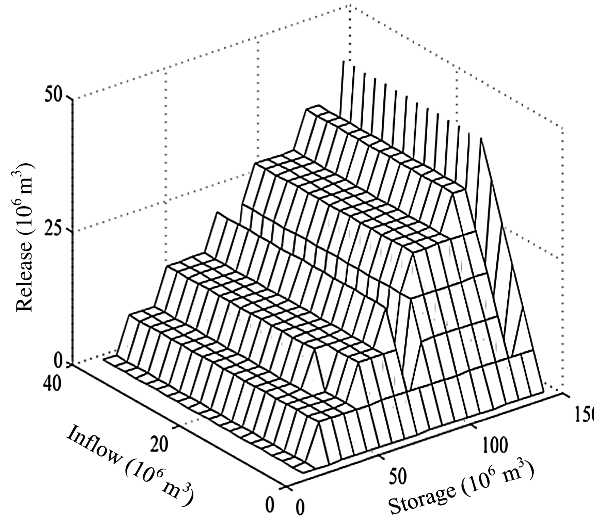

Fig. 8. Optimal operation rule curve for October on the basis of Scenario 3

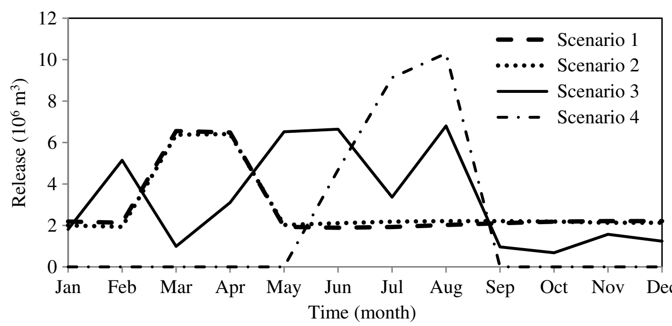

Fig. 9. Optimal release volume for each of the four scenarios

did not change dramatically by increasing water demand for a given storage volume. The values of releases for the classes of demand were on the basis of the storage volume classes; whenever the storage volume increased, so did the water supply.

The optimal release volumes for each scenario during the drought year are displayed in Fig. 9. The optimal releases and volumes of water-demand deficit are listed in Table 4 for all scenarios.

The objective function's values and the values of the performance indices values for each scenario are listed in Table 5. The ratio of each scenario's objective function value to the total value of the sum of the four objective functions is shown in Fig. 10. Fig. 10 shows that the calculated ratio values of each of the four scenarios were very similar to each other, and the difference between the highest calculated ratio (the worst) and the lowest ratio (the best) was only 6%, which indicates little difference between the objective functions' values of the four scenarios. Fig. 11 depicts the values of the performance indices for each scenario. The performance of the calculated operation policy using the proposed SDP method with inflow and water demand uncertainties was compared with those of the three other scenarios. According to Table 5, and on the basis of the calculated objective function's values of Scenario 1 and 2, it is evident that instead of considering water demand uncertainty, assuming known values for water demand in Scenario 2 improved the objective function by 1.28% relative to that of Scenario 1. In addition, the performance indices in Fig. 11 for Scenarios 1 and 2 were the same. Using the operation rules of Scenario 2 in a period with known water demand led to a better objective value than that of Scenario 1, yet, using the operating rules of Scenario 2 in future periods is futile because the values of water demand are unknown. The agricultural demand values changed continuously during the operation period and these values have uncertain and stochastic nature. Therefore, assuming known values of agricultural water demand in future periods is not feasible. Hence, the operating rules of Scenario 1 (developed with SDP) can be applied to every period generally because it simultaneously considered inflow and water demand uncertainties.

Considering known reservoir inflow volumes in Scenario 3 improved the objective function by 18.35% relative to that of Scenario 1, and according to Fig. 11, the volumetric reliability index in Scenario 3 was just 6% better than that of Scenario 1, whereas the time-based reliability and vulnerability indices in Scenario 3 were 8 and 3% worse than those of Scenario 1, respectively. Because the difference between the objective functions' values of Scenarios 1 and 3 was 14.33 times the difference of the objective functions' values of Scenarios 1 and 2, the effect of inflow uncertainty on operating policy was more pronounced than that of water demand uncertainty. It is clear that when the inflow volume for a period was known, using the operating policy of Scenario 3 produced a superior objective function for the period. Yet, these rules cannot be applied in future periods when the inflow volume is unknown because the values of variables that influence the reservoir system performance cannot be specified accurately.

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Table 4. Release (R) and Deficit Volumes for Each Scenario

	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
Month	R (10^6 m^3)	Deficit (10^6 m^3)	R (10^6 m^3)	Deficit (10^6 m^3)	R (10^6 m^3)	Deficit (10^6 m^3)	R (10^6 m^3)	Deficit (10^6 m^3)
January	2.19	0.00	1.99	0.00	1.81	0.00	0.00	0.03
February	2.13	0.00	1.93	0.00	5.14	0.00	0.00	0.03
March	6.55	0.00	6.37	0.00	0.99	0.00	0.00	0.03
April	6.49	0.00	6.41	0.00	3.10	2.08	0.00	5.19
May	1.93	18.69	2.02	18.59	6.52	14.1	0.00	20.62
June	1.89	30.18	2.10	29.96	6.64	25.42	4.68	27.39
July	1.92	34.59	2.18	34.32	3.363	33.14	9.13	27.38
August	2.02	35.66	2.20	35.47	6.8	30.88	10.3	27.38
September	2.11	20.37	2.20	20.27	0.96	21.51	0.00	22.48
October	2.18	4.37	2.18	4.36	0.68	5.86	0.00	6.55
November	2.21	0.00	2.12	0.00	1.573	0.00	0.00	0.03
December	2.21	0.00	2.12	0.00	1.23	0.00	0.00	0.03

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Table 5. Value of the Objective Function and the Performance Indices for Each Scenario

	Number of scenario			
Index	1	2	3	4
f	4,163.32	4,110.02	3,399.23	3,249.92
RV	0.11	0.11	0.17	0.15
$RT_{100\%}$	0.50	0.50	0.42	0.00
$\varphi_{100\%}$	0.17	0.17	0.14	0.083

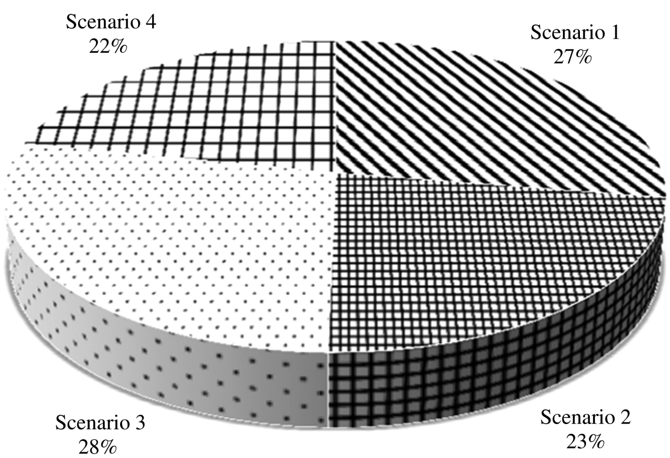

Fig. 10. Percentage of each objective function of the sum of the four objective functions

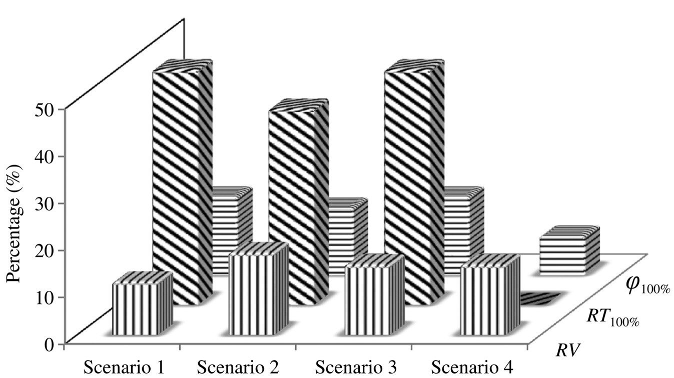

Fig. 11. Performance indices for each scenario

The solution space in Scenario 4 was continuous and all the variables were known in comparison with the proposed SDP method (Scenario 1) whose solution space was discretized (20 classes for reservoir storage volume, inflow volume, and water demand volume). Therefore Scenario 4 is considered a global optimal solution in this research. The global optimal objective function of Scenario 4 was only 21.93% better than the objective function of Scenario 1, and the volumetric vulnerability index was only 4% better than that of Scenario 1, whereas the time-based reliability and vulnerability indices were 50 and 8.7% worse than those of Scenario 1, respectively. Specifying known reservoir inflow and agricultural water demand in future periods using the *Lingo 11.0* model is not feasible because of the uncertain nature of these variables. The global optimal solution using Scenario 4 is contingent on knowing the values of all variables. Reservoir operation requires optimal operating policies that can be used in every period and in every climatic condition. The developed SDP method calculates operation policies that are applicable in future periods when considering the uncertainty of inflow and water demand volumes. For these reasons Scenario 1 (from the proposed SDP) has general applicability. The fact that the difference between the global optimal objective function (Scenario 4) and the objective function of Scenario 1 was so low indicates the excellent performance of the proposed SDP method.

Concluding Remarks

Reservoir inflow and water demand volumes have pronounced variability in different months of a year (monthly scale) and in different years (annual scale). This research developed a SDP method that simultaneously includes inflow and water demand uncertainties in the derivation of reservoir operation rules. Three other scenarios were defined to evaluate the applicability of the developed SDP, and to calculate optimal releases during a drought year using operating rules corresponding to each the four scenarios entertained in this work. The objective functions and performance indices of the four scenarios were compared. The global optimal objective function (whose solution space was continuous and all variables were known) was only 21.93% better than that of the developed SDP method. Achieving the global optimal is infeasible because the values for inflow and water demand cannot be specified accurately. These results demonstrate that the developed SDP method captures the uncertainty of natural phenomena and it has superior applicability relative to the considered deterministic models. The developed SDP method has generality and is applicable in every operation period and climatic condition.

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