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Incorporating ecological requirement into multipurpose reservoir operating rule curves for adaptation to climate change

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SUMMARY

Operating rule curves have been widely applied to reservoir operation, due to their ease of implementation. However, these curves excluding ecological requirement are generally derived from observed or synthetic flows and have rarely been determined by future flows under climate change. This paper develops an integrated adaptive optimization model (IAOM) for derivation of multipurpose reservoir operating rule curves including ecological operating rule curve under future climate change. Steps in the proposed IAOM include: (1) weather generator module to generate feasible future climate conditions, (2) VIC model as the hydrological simulation module to generate streamflows from those future weather conditions, and (3) multipurpose reservoir optimization module to determine the optimal reservoir operations to deal with climate change. China's Danjiangkou reservoir in Han River basin is selected for a case study. The results demonstrate that the IAOM provides optimal multipurpose reservoir operating rule curves that reflect the hydrologic characteristics of future climate change. Ecological supply water operation will alleviate negative effect of dam on river ecosystem without reducing conservation benefits and flood control standard. Therefore, they can consult with reservoir administrators if it is useful results for operations.

1. Introduction

Reservoirs are among the most efficient tools for integrated water resource development and management. With the rapid economic development, the role of reservoirs has become more and more important to meet society's energy and water requirements. By altering the spatial and temporal distribution of runoff, reservoirs serve many purposes, such as flood control, hydropower generation, navigation, recreation and ecology (Guo et al., 2004).

Operating rule curves are able to express the operation strategy in a visual way (Chang et al., 2005). Moreover, operating rule curves are subject to some implicit constraints, such as the continuity between reservoir consecutive time periods and the monotonically increasing relationship between reservoir release and storage (Liu et al., 2011c). These advantages enable the operating rule curves to be widely applied in practice. A method involving optimization, fitting and refinement has been adopted to obtain the optimal refill rules for single purpose (Liu et al., 2006) and multi-purpose (Liu et al., 2011c) in China's Three Gorges Reservoir. Additionally, some new optimization algorithms, such as genetic algorithms (Oliveira and Loucks, 1997; Wardlaw and Sharif, 1999; Chang et al., 2005; Chen et al., 2007a,b; Cheng et al., 2008; Hınçal et al., 2011; Liu et al., 2011a,b) and particle swarm optimization (Reddy and Kumar, 2007; Ostadrahimi et al., 2012) have been used to optimize reservoir operation rules. However, these operating rule curves are generally derived from observed or synthetic flows and have rarely been determined by future flows under climate change. For quite some time a question of climate change impacts on reservoir operating rule curves has been investigated in the literature. Fowler et al. (2003) studied the impacts of climatic change and variability on water resource reliability, resilience, and vulnerability of the Yorkshire water resource system by modeling changes to weather type frequency, mean rainfall statistic, and potential evapotranspiration. Buttle et al. (2004) studied the impact of changes in the lake levels and flows of the Great Lakes in terms of the hydro-electric power produced. Arnell and Delaney (2006) examined adaptation to climate change by water supply companies in England and Wales. Brekke et al. (2009) developed a risk assessment framework and applied it to California's Central Valley Project and State Water Project systems. Li et al. (2009) investigated potential impacts of future climate change on streamflow and reservoir operation performance in a Northern American Prairie watershed. Lopez et al. (2009) used perturbed physics ensembles of climate models for impacts analysis and planning for public water supply in England under climate

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change. The impacts of reservoir operations under climate change have been investigated for small reservoirs (Krol et al., 2011) and multi-purpose reservoirs (Raje and Mujumdar, 2010) to estimate water availability for current and possible future conditions. Eum and Simonovic (2010) proposed an integrated reservoir management system for a Korean river basin to examine how monthly rule curves are changed by future hydrologic conditions. In monthly rule curves, flood damage is estimated indirectly by the amount of reservoir spill even though the damage in most cases occurs downstream from the reservoir (Eum et al., 2012).

In much of the existing and quite limited research only current reservoir operating rules excluding ecological requirement are used to determine how reservoir operation will respond to climate change (Wood et al., 1997; Eum and Simonovic, 2010). Besides, reservoir operation, when involved into riverine ecosystem problems, its negative effect on river ecosystem is always claimed by ecologists (Harman and Stewardson, 2005; Lee and Chang, 2005; Suen and Eheart, 2006; Yang et al., 2012). So it is necessary to incorporate ecological operating rule curve into multipurpose reservoir operating rule curves to avoid or at least alleviate the negative impacts of dams on river ecosystem under future climate change. Therefore, this paper presents an integrated adaptive optimization model (IAOM) for derivation of multipurpose reservoir operating rule curves including ecological operating rule curve under future climate change. The IAOM is developed for assisting the process of adaptation of existing reservoirs to climate change. It includes (1) weather generator module to generate feasible future climate conditions, (2) VIC model as the hydrological simulation module to generate streamflows from those future weather conditions, and (3) multipurpose reservoir optimization module to determine the optimal reservoir operations to deal with climate change. China's Danjiangkou reservoir in Han River basin has been used to illustrate the implementation of the IAOM developed in this study.

The aim of the paper is to explore how multipurpose reservoir operating rule curves adapt to future climate change, not to demonstrate whether climate variations are large enough to be taken into account in management of water systems. The paper is organized as follows. The next section provides the description of the IAOM and the methodological aspects of GCM weather generator, hydrologic and multipurpose reservoir optimization modules. The following section illustrates the application of the IAOM using China's Danjiangkou reservoir in Han River basin as a case study. The paper ends with the presentation of conclusions and an outline of future work.

2. The integrated adaptive optimization model

The integrated adaptive optimization model (IAOM) consisted of following three separately developed modules: (1) weather generator module to generate feasible future climate conditions, (2) VIC model as the hydrological simulation module to generate streamflows from those future weather conditions, and (3) multipurpose reservoir optimization module to determine the optimal reservoir operations to deal with climate change.

The structure of the IAOM is described in Fig. 1. The details of each module are given as follows.

2.1. Weather generator module

General circulation models (GCMs), which describe atmospheric processes by mathematical equations, are one of the most important tools for studying the impact of climate change. Statistical downscaling aims to derive empirical relationships that transform large-scale features of the GCM (predictors) to regional-scale variables (predictands), such as precipitation and temperature (Tripathi et al., 2006).

Support vector machine (SVM) is a new machine study method based on statistical learning theory and stresses for studying statistical learning rules under small sample conditions (Vapnik, 1998). SVM solves many practical problems, such as small-sample, nonlinear, high dimension number and global minimum points, by using a structural risk minimization principle. Recently, SVM has been widely applied in the fields of hydrological classification and regression analysis (Tripathi et al., 2006; Chen and Yu, 2007). However, it has some drawbacks in dealing with the large-sample data, such as slow training speed, low implementation efficiency and inadaptability to noise. To overcome the drawbacks of the SVM for large-sample data, Lee et al. (2005) proposed a new smoothing strategy for solving regression of the large-scale

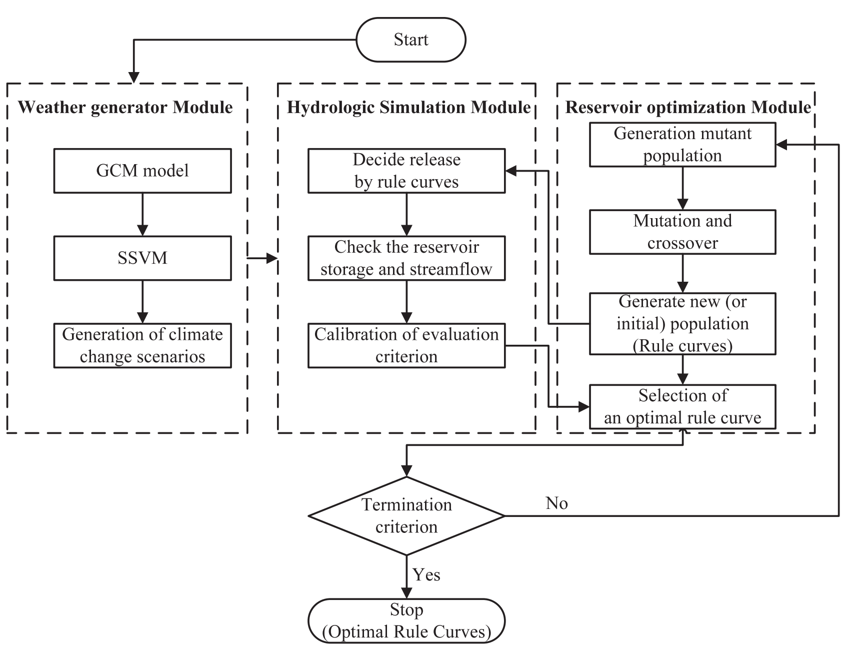


Fig. 1. Structure of the IAOM.

training data, called smooth support vector machine (SSVM), which has been verified as more efficient than the SVM algorithm mentioned above. The inequality constraint problem of SVM is replaced by an unconstrained problem and the SSVM has a unique global optimal solution. The detailed introduction of SVM and SSVM algorithms have been described by Lee et al. (2005), Tripathi et al. (2006) and Chen and Yu (2007). A tuning procedure which can automatically optimize parameters (Lee et al., 2005) is applied in this study to estimate the parameters of SSVM. SSVM (Lee et al., 2005; Chen et al., 2009; Guo et al., 2009) is used to predict climate change impact in this paper.

It is one of the most important steps in a downscaling exercise to select appropriate predictors, or characteristics from GCMs. The mean sea level pressure (MSLP), surface air temperature (2 m), 500 h Pa geopotential height (GH) and specific humidity (SH), and 850 h Pa GH and SH were selected as the predictors for predicting precipitation; 850 h Pa temperature (TEM) and MSLP were considered as the predictors for predicting temperature (Wilby et al., 1999). Therefore, the statistical downscaling of GCMs outputs (Chen et al., 2009; Guo et al., 2009) to obtain input of hydrological simulation model for studying hydrological consequences of climate change is applied in this study.

2.2. Hydrologic simulation module

Various climate conditions obtained using GCMs are used as input into the hydrologic model in order to further assess the impacts of climate change on local conditions in a basin. Hydrologic models are mathematical representations of rainfall–runoff processes operating within a basin. They provide essential information for management of storage facilities–reservoirs in the basin.

Distributed hydrological models have the ability to produce simulations of spatial patterns of hydrological response due to soil, vegetation, land-use, precipitation, evaporation and runoff; furthermore, the gridded structure of the models can be easily coupled with GCMs. Therefore, the statistical downscaling of GCMs outputs as input to distributed hydrological models to assess the effects of climate change has been recognized by many authors (Xu, 1999; Wilby et al., 2006; Manoj et al., 2006; Ghosh and Mujumdar, 2008) and will become the best approach for climate change impact studies.

The Variable Infiltration Capacity (VIC) distributed hydrological model is a macro-scale hydrological model based on a soil–vegetation–atmosphere transfer scheme, which is designed to describe the land surface in numerical weather prediction and climate, describe the variation and transfer of water and energy (Liang et al., 1994). The VIC model has one kind of bare soil and different vegetation types in each grid cell. It includes both the saturation and infiltration excess runoff processes in a grid cell with a consideration of the sub grid-scale soil heterogeneity, and the frozen soil processes for cold climate conditions. Three types of evaporation: evaporation from wet canopy, evapotranspiration from dry canopy and evaporation are considered. The one dimensional Richard equation is used to describe the vertical soil moisture movement and the moisture transfer between soil layers obeys the Darcy law. The ARNO method is used to describe baseflow which takes place only in the lowest layer. The routing model represented by the unit hydrograph method for overland flow and the linear Saint-Venant method for channel flow, allow runoff to be predicted (Liang et al., 1994). Yuan et al. (2004) applied the VIC model to simulating the daily runoff in the Hanjiang basin of China and compared with the daily and monthly observed streamflow at six stations. Yuan et al. (2005) applied the VIC model to simulating future water resources at the Haihe River Basin in China in response to climate change scenarios. Xie et al. (2007) presented a methodology for regional parameter estimation of the VIC model with the goal of improving the streamflow simulation for river basins in China. The VIC model was established and calibrated to predict climate change impact in the Han River basin of China (Guo et al., 2009). For the implementation with the IAOM, therefore, the runoff as input of the multipurpose reservoir optimization module is simulated by the VIC model with the downscaled precipitation and temperature time series.

2.3. Multipurpose reservoir optimization module

2.3.1. The objective functions

The proposed optimization model has five different objective functions which are described in the following section.

(1) Minimizing flood control risk for downstream

$$f_1 = \min R = \max \frac{\#(Qx_t \leqslant Q_{an})}{T} \tag{1}$$

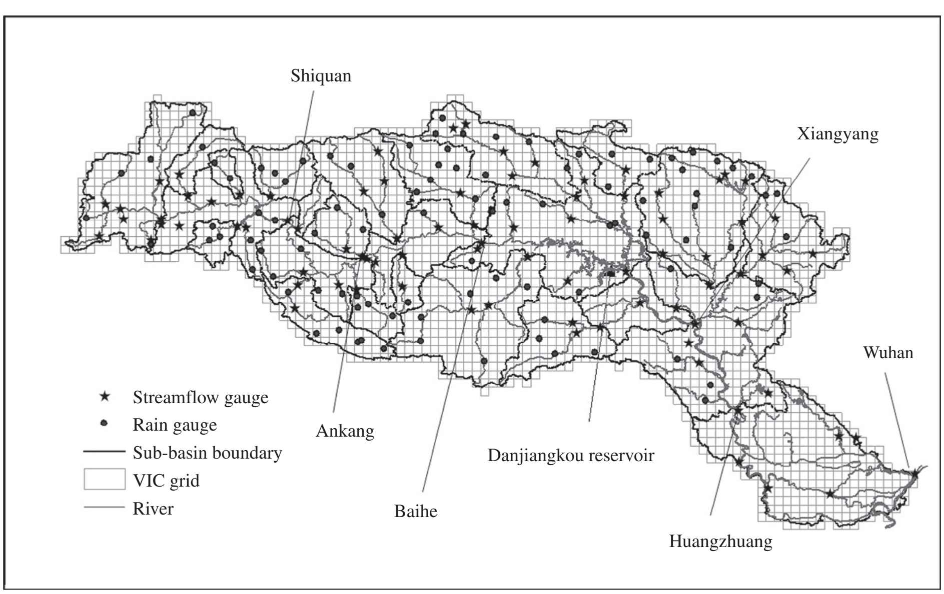


Fig. 2. Characteristics of the Han River basin for VIC model.

(2) Maximizing water demand for downstream (WDD)

$$f_2 = \max W_R = \max \frac{1}{N} \sum_{t=1}^{T} Q_{Rt} \Delta t \tag{2}$$

(3) Maximizing water diversion (WD)

$$f_3 = \max W_D = \max \frac{1}{N} \sum_{t=1}^{T} Q_{Dt} \Delta t \tag{3}$$

(4) Maximizing power generation (PG)

$$f_4 = \max E = \max \frac{1}{N} \sum_{t=1}^{T} P_t \Delta t \tag{4}$$

(5) Maximizing ecological water demand (EWD)

$$f_5 = \max W_C = \max \frac{1}{N} \sum_{t=1}^{T} Q_{Ct} \Delta t \tag{5}$$

Table 1
List of characteristic parameter values of Danjiangkou reservoir.

Reservoir	Unit	Danjiangkou
Total storage	billion m^3	33.91
Flood control storage in summer	billion m^3	14.10
Flood control storage in autumn	billion m^3	11.10
Crest elevation	m	176.6
Normal pool water level	m	170.0
Flood limited water level in summer	m	160.0
Flood limited water level in autumn	m	163.5
Dead water level	m	150.0
Fluctuating water level	m	145.0
Install capability	MW	900.0
Annual generation	billion kW h	3.8
Regulation ability	–	Multi-years

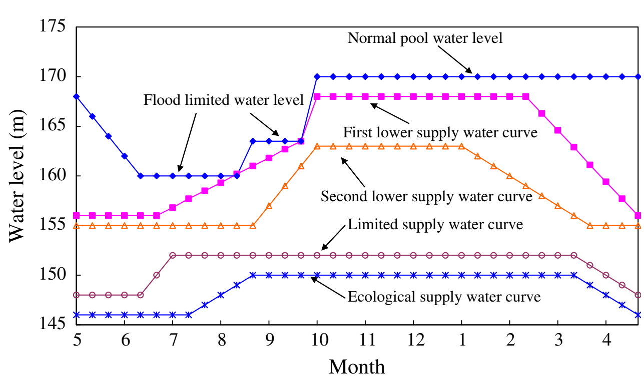


Fig. 3. Designed operating rule curves of Danjiangkou reservoir.

2.3.2. Subject to the following constraints

The objective functions subject themselves to following constraints: (1) water balance equation, (2) reservoir water level limits, (3) comprehensive utilization of water required at downstream reservoir limits, (4) power generation limits, (5) boundary conditions limit (Liu et al., 2006, 2011a,b,c).

where

f_i	the ith objective function value
R	the flood control risk for downstream, %
W_R	the water demand for downstream, m^3
W_D	the water diversion, m^3
E	the power generation, kW h
W_C	the water demand for ecology, m^3
T	the number of periods
Δt	the interval of time
Q_{Rt}	the water demand flow for downstream in period t, m^3/s
Q_{Dt}	the water diversion flow in period t, m^3/s
Q_{Ct}	the water demand flow for ecology in period t, m^3/s
Q_{an}	the maximum discharge in period t, m^3/s
Qx_t	the sum of reservoir outflows in period t, m^3/s
P_t	output power of reservoir in period t, kW

2.3.3. Optimization algorithm

The integer and real parameters for joint operation rule curves can be optimized using heuristic methods. Since the adaptive genetic algorithm (AGA) has a powerful ability both in theoretical (Srinivas and Patnaik, 1994) and practical problems (Chang et al., 2005; Asiabar et al., 2010), it was selected as the optimization algorithm in this study. The AGA provides three encoding methods, real, binary and a hybrid of these two types. The hybrid encoding method was used in the optimization procedure due to the predefined operation guide curves.

3. Case study

3.1. The Han River basin

The Han River basin is the largest tributary of the Yangtze River; it passes through the provinces of Shanxi and Hubei of China, and merges into the Yangtze River at Wuhan city. The river's length is 1570 km and the basin area is 159,000 km^2. The basin has a subtropical monsoon climate and has, as a result, dramatic diversity in its water resources. Annual precipitation varies from 700 mm to 1100 mm, of which 70–80% of the total amount occurs in the wet season from May to September.

The Han River basin plays critical roles in the flood control and water supply in China. The Danjiangkou reservoir located in the middle reach of the Han River basin (Fig. 2) is the source of water for the middle route of the South–North Water Diversion Project,

Table 2
The operational results of different operating rule curves schemes in current years.

Evaluation criterion	DORCS				OORCS		
	P0	P1	P2	P3	P1	P2	P3
Mean annual WDD (billion m^3)	11.78	10.02	10.73	11.13	9.33	10.43	10.98
Lack of mean annual WDD (billion m^3)	0.00	1.76	1.05	0.65	2.45	1.34	0.80
Assurance probability of WDD (%)	100.00	79.94	87.19	91.28	76.93	87.58	91.74
Mean annual WD (billion m^3)	10.52	6.39	7.52	8.23	6.15	7.23	8.12
Lack of mean annual WD (billion m^3)	0.00	3.31	2.18	1.47	3.55	2.47	1.58
Mean annual PG (billion kW h)	2.65	3.92	3.74	3.61	4.03	3.83	3.65
Mean annual WVPG (billion m^3)	15.52	25.94	24.07	22.71	26.00	24.20	22.80
Mean annual EWD (billion m^3)	\	15.52	12.65	10.46	16.23	13.01	10.64
Lack of mean annual EWD (billion m^3)	\	0.83	0.38	0.18	0.12	0.02	0.00
Assurance probability of EF (%)	\	86.27	92.90	95.83	97.99	99.54	100.00

and the Jianghan plain in the lower basin is one of the most important bases for commodity grain production. The available water resources in Han River basin and the impact of water diversion have been discussed by many authors (Guo et al., 2002; Chen et al., 2007). The characteristic parameter values of Danjiangkou reservoir are given in Table 1.

The designed operating rules can be regarded as a standard operating policy. The designed operating rule curves of the Danjiangkou reservoir are shown in Fig. 3. From the end of May to the middle of August, the reservoir water level will be lowered to 160 m (flood limited water level in summer). From the end of August to the end of September, the reservoir water level will be raised to 163.5 m (flood limited water level in autumn). In October, the reservoir water level will be raised gradually to the normal pool level of 170 m. From November to the end of April in the following year, the reservoir water level should be kept at as high as possible to generate more electrical power. The reservoir water level will be lowered further, but should not fall below 145 m before the end of April to satisfy navigation conditions.

3.2. Results

3.2.1. Estimating ecological flow based on Tennant method

Tennant described a quick, easy methodology for determining flows to protect the aquatic resources in both warm water and coldwater streams, based on their average flow (Tennant, 1976). Since the Tennant method has a powerful ability of practical problems in China (Yang et al., 2012), it is selected as estimating ecological flow (EF) in this study. Therefore, the EF is estimated using Tennant method with 40-year observed inflows (current years from 1961 to 2000) and time interval is 10 days. The EFs in different schemes are regarded as the minimum water discharge constrain for Danjiangkou reservoir. The schemes P0, P1, P2, and P3 denote EF as none (0% of average flow in flood and non-flood season), abundant (50% of average flow in flood season, 30% of average flow in non-flood season), well (40% of average flow in flood season, 20% of average flow in non-flood season), and poor (30% of average flow in flood season, 10% of average flow in non-flood season), respectively.

3.2.2. Multipurpose reservoir operating rule curves optimization problem

In order to compromise between flood control and conservation for reservoir operation, a multi-objective problem can be transformed into a single objective problem using weighting factors that measures the important of each objective (Li et al., 2009; Raje and Mujumdar, 2010; Eum and Simonovic, 2010; Eum et al., 2012). Therefore, in this study we formulate the multi-objective functions to single objective function as shown in

$$\max F = \max \sum_{i=1}^{M} \alpha_i f_i' \tag{6}$$

The sub-objective function f_i should be normalized, whereby each average of sub-objective function $\bar{f}_i$ is divided by f_i derived by the designed operating rule curves as shown in

$$f_i' = \bar{f}_i / f_i \tag{7}$$

Values of the AGA's parameters must be defined before the algorithm is used. These parameters include the sample-size population and the probabilities of crossover and mutation. Although it is important to determine the best parameter values, and several studies have tried to do so (DeJong, 1975; Grefenstette, 1986; Schaffer et al., 1989), no universal rules have yet been found. In this circumstance, one relies on experience and trial-and-error to find a good set of parameter values. The suggested sets of values (Srinivas and Patnaik, 1994) that consistently lead to good results in this study are shown in the following: population size = 100, maximum iteration = 100, crossover probability P_c and mutation rate P_m are computed by Eqs. (8) and (9), respectively.

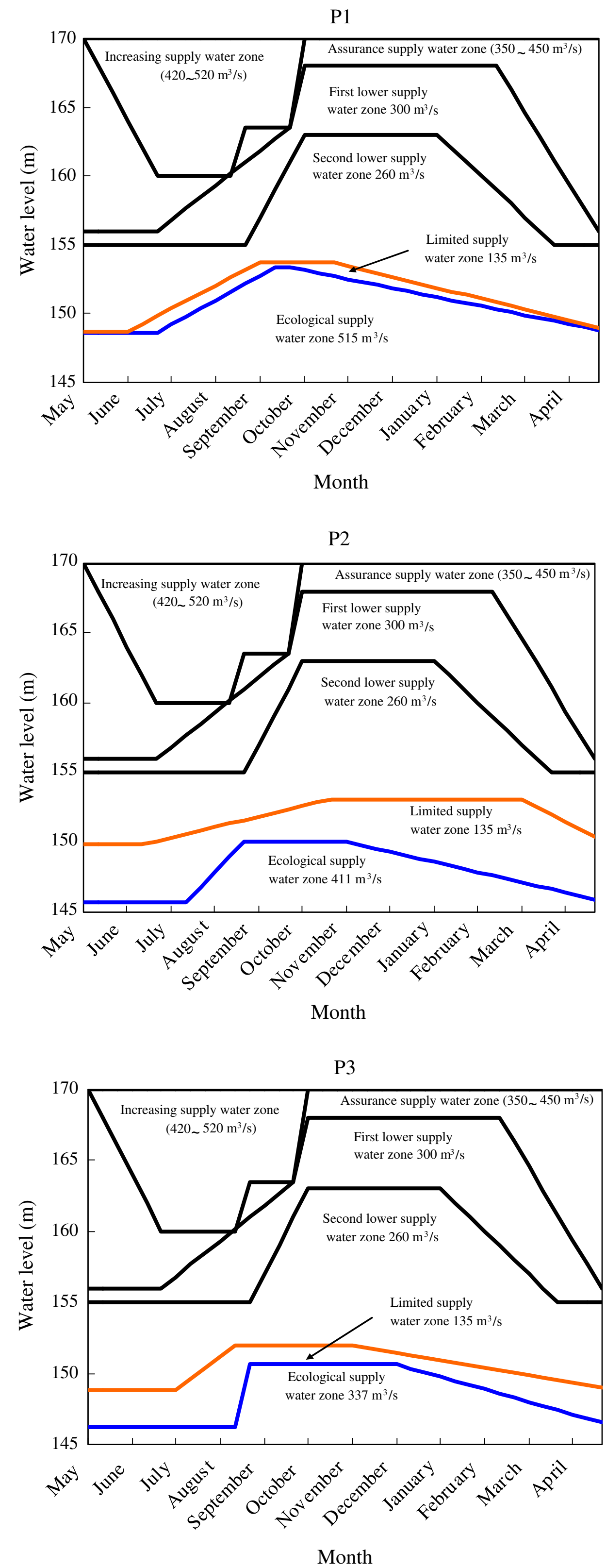


Fig. 4. Optimal operating rule curves of different ecological flow schemes in current years.

$$P_c = \begin{cases} \varepsilon_1 (f_{\max} - f_c)/(f_{\max} - f_{avg}) & f_c \geqslant f_{avg} \\ \varepsilon_3 & f_c < f_{avg} \end{cases} \tag{8}$$

$$P_m = \begin{cases} \varepsilon_2 (f_{\max} - f_m)/(f_{\max} - f_{avg}) & f_m \geqslant f_{avg} \\ \varepsilon_4 & f_m < f_{avg} \end{cases} \tag{9}$$

where

F	the fitness function
f_i'	the normalized sub-objective functions
$\bar{f_i}$	the average of sub-objective function
α_i	the weighting factors
ε_i	the random variables in interval [0,1]
f_c	the maximum fitness between two crossover children
f_m	the maximum fitness between two mutation children
f_{avg}	the average population fitness
$f_{\max}$	the maximum population fitness

Flood control objective is obliged to satisfy with a reliability of 100%. Therefore, the objective function of flood control risk for downstream is transformed into constraint as $Qx_t \leqslant Q_{an}$. The values α_2, α_3, α_4 and α_5 have been determined according to the dam's administrative recommendations, and demands pattern history of study area. To reveal the effect of ecological objective for other objectives, only the lower basic guide curve and the ecological guide

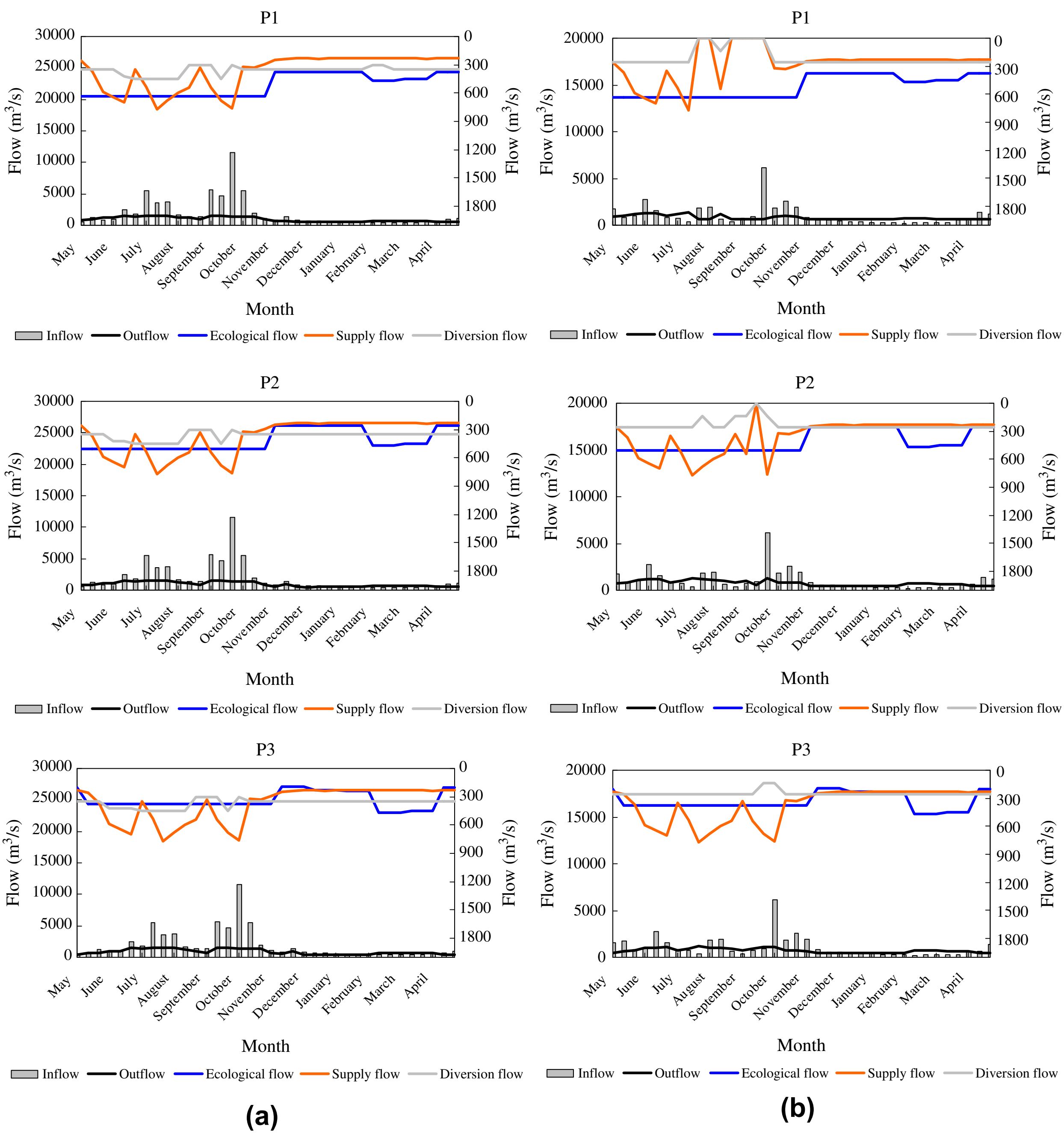


Fig. 5. Optimum reservoir releases in wet, normal, and dry year. (a) Wet. (b) Normal. (c) Dry.

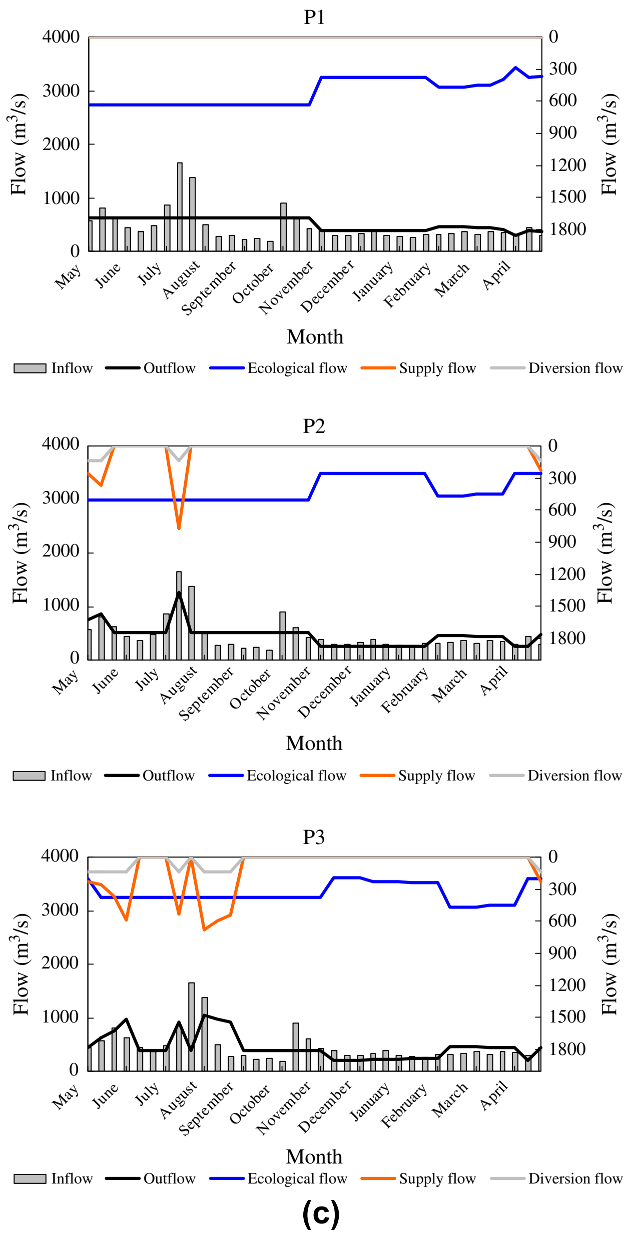


Fig. 5 (*continued*)

curve in Fig. 3 are selected as optimal operating rule curves. Therefore, different values (e.g., $\alpha_2 = 0.20$, $\alpha_3 = 0.20$, $\alpha_4 = 0.10$, $\alpha_5 = 0.50$) are assumed for α_i in this study. The optimization problem formulated determines the optimal set of annual rule curves for Danjiangkou reservoir with the inflow of base years compared to the designed operating rule curves. The operational results of the optimal operating rule curves scheme (OORCS) and the designed operating rule curves scheme (DORCS) are listed in Table 2. Table 2 shows that: (1) For DORCS, WDD and WD are satisfied, but PG and water volume of power generation (WVPG) are less in scheme P0 compared to other schemes. Mean annual WDD and mean annual WD are increased, assurance probability of EF is high, and lack of mean annual EWD is less with the decreasing EWD in schemes P1, P2, and P3. WDD, WD and EWD are all unsatisfied because Danjiangkou reservoir often operates nearly in dead water level or water-level-fluctuating zone at the end of supply water season in scheme P1. Though assurance probability of EF is increased in schemes P2 and P3, both WDD and WD are unsatisfied. Therefore, the Danjiangkou reservoir can never satisfy WDD, WD, and EWD in DORCS under the current inflows from 1961 to 2000; (2) OORCS supplies 0.71 billion m^3 (or increase 4.57%), 0.36 billion m^3 (or increase 2.85%), and 0.18 billion m^3 (or increase 1.72%) more mean annual EWDs than DORCS in schemes P1, P2, and P3 and assurance probabilities of EF in OORCS are increased from 86.27%, 92.90%, and 95.83% to 97.99%, 99.54%, and 100.00% compared to DORCS in schemes P1, P2, and P3. Mean annual WDD and mean annual WD of OORCS in scheme P1 nearly decrease 0.7 billion m^3 and 0.3 billion m^3 than those of DORCS in scheme P1, however, decreases for mean annual WDD and mean annual WD of OORCS in schemes P2 and P3 have not exceeded 0.3 billion m^3 than those of DORCS in schemes P2 and P3. Besides, OORCS can generate 0.11 billion kW h, 0.09 billion kW h, and 0.04 billion kW h more power (or increase 2.81%, 2.41%, and 1.11%) than DORCS in schemes P1, P2, and P3. In summary, OORCS can effectively increase assurance probability of EF and hydropower generation with small reduction of WDD and WD compared to DORCS.

As a further visual analysis, multi-objective optimal operating rule curves of different ecological flow schemes are shown in Fig. 4. Fig. 4 shows that the heights of the lower basic guide curve and the ecological guide curve reduce with the decreasing EWD in schemes P1, P2, and P3. Flows of ecological supply water zone are 515 m^3/s, 411 m^3/s, and 337 m^3/s, respectively in schemes P1, P2, and P3.

In order to reveal the practical effect of multi-objective optimal operating rule curves in Danjiangkou reservoir, the inflows of three typical hydrologic years, i.e. wet (1984), normal (1970) and dry (1999) year are selected as comparative study. The optimum reservoir releases using multipurpose optimal operating rule curves in the wet, normal and dry years are shown in Fig. 5. Fig. 5a shows that EWDs are all satisfied, and the differences of WDD and WD are insignificant in wet year among the schemes P1, P2, and P3. Fig. 5b and c shows that the practical effect of multi-objective optimal operating rule curves is marked, and WDD, WD and assurance probability of EF are increased with the decreasing EWD in normal and dry years among the schemes P1, P2, and P3. The possible reasons are explained as follows:

Table 3
The simulated results of some hydrological stations under the A2 scenarios of CGCM2.

Hydrological stations	CGCM2						
	Current years (billion m^3)	Future years					
		2020s (billion m^3)	Change rate (%)	2050s (billion m^3)	Change rate (%)	2080s (billion m^3)	Change rate (%)
Shiquan	9.04	7.66	−15.30	8.44	−6.69	11.59	28.16
Ankang	15.76	13.18	−16.37	15.30	−2.93	21.21	34.63
Baihe	22.72	18.55	−18.35	21.74	−4.31	30.43	33.91
Danjiangkou	38.07	31.72	−16.69	37.59	−1.27	50.80	33.43

Table 4
The simulated results of OORCS in current years and DORCS for 2020s, 2050s, and 2080s.

Years	Evaluation criterion	DORCS				OORCS in current years		
		P0	P1	P2	P3	P1	P2	P3
2020s	Mean annual WDD (billion m^3)	11.78	7.85	9.00	9.97	8.59	9.98	10.95
	Lack of mean annual WDD (billion m^3)	0.00	3.93	2.78	1.81	3.19	1.80	0.83
	Assurance probability of WDD (%)	100.00	65.51	76.31	84.34	71.91	84.26	91.59
	Mean annual WD (billion m^3)	10.12	4.92	6.28	7.05	5.84	6.83	7.94
	Lack of mean annual WD (billion m^3)	0.00	4.78	3.42	2.65	3.86	2.87	1.76
	Mean annual PG (billion kW h)	2.43	3.34	3.21	3.03	3.40	3.24	3.04
	Mean annual WVPG (billion m^3)	14.46	22.15	20.94	19.28	22.71	21.24	19.43
	Mean annual EWD (billion m^3)	/	12.96	10.35	7.54	13.46	10.53	7.55
	Lack of mean annual EWD (billion m^3)	/	0.71	0.30	0.10	0.20	0.13	0.09
	Assurance probability of EF (%)	/	92.67	96.68	98.61	96.60	99.61	99.69
2050s	Mean annual WDD (billion m^3)	11.78	8.91	10.25	10.77	9.18	10.6	11.39
	Lack of mean annual WDD (billion m^3)	0.00	2.86	1.53	1.01	2.59	1.18	0.39
	Assurance probability of WDD (%)	100.00	73.69	85.8	90.35	77.08	88.04	94.68
	Mean annual WD (billion m^3)	10.47	6.27	7.30	8.16	6.50	7.53	8.67
	Lack of mean annual WD (billion m^3)	0.00	3.43	2.40	1.54	3.20	2.17	1.03
	Mean annual PG (billion kW h)	2.61	3.68	3.55	3.33	3.74	3.59	3.34
	Mean annual WVPG (billion m^3)	15.40	24.15	22.88	20.85	24.60	22.96	20.90
	Mean annual EWD (billion m^3)	/	14.71	11.75	8.54	15.27	11.92	8.55
	Lack of mean annual EWD (billion m^3)	/	0.69	0.26	0.07	0.13	0.09	0.06
	Assurance probability of EF (%)	/	93.60	97.15	99.31	96.06	98.84	99.54
2080s	Mean annual WDD (billion m^3)	11.78	10.39	10.58	11.57	10.55	10.86	11.61
	Lack of mean annual WDD (billion m^3)	0.00	1.38	1.20	0.20	1.23	0.92	0.17
	Assurance probability of WDD (%)	100.00	88.35	91.97	97.99	88.89	94.68	98.15
	Mean annual WD (billion m^3)	11.10	7.41	8.60	9.27	7.87	8.90	9.77
	Lack of mean annual WD (billion m^3)	0.00	2.29	1.10	0.43	1.83	0.80	0.00
	Mean annual PG (billion kW h)	3.23	4.43	4.11	3.99	4.44	4.27	4.01
	Mean annual WVPG (billion m^3)	18.67	28.36	24.66	24.28	28.52	26.69	24.33
	Mean annual EWD (billion m^3)	/	19.90	15.77	11.40	20.00	19.93	11.41
	Lack of mean annual EWD (billion m^3)	/	0.57	0.38	0.05	0.46	0.57	0.04
	Assurance probability of EF (%)	/	95.91	97.30	98.53	97.22	97.72	99.91

Table 5
The optimal results of IAOM in 2020s, 2050s, and 2080s.

Years	Evaluation criterion	P1	P2	P3
2020s	Mean annual WDD (billion m^3)	9.75	10.58	11.19
	Lack of mean annual WDD (billion m^3)	2.02	1.19	0.59
	Assurance probability of WDD (%)	76.23	85.57	93.21
	Mean annual WD (billion m^3)	6.18	7.04	8.07
	Lack of mean annual WD (billion m^3)	3.52	2.66	1.63
	Mean annual PG (billion kW h)	3.70	3.48	3.35
	Mean annual WVPG (billion m^3)	24.19	22.45	21.32
	Mean annual EWD (billion m^3)	13.62	10.64	7.63
	Lack of mean annual EWD (billion m^3)	0.05	0.02	0.01
	Assurance probability of EF (%)	99.00	99.69	99.92
2050s	Mean annual WDD (billion m^3)	10.16	10.90	11.47
	Lack of mean annual WDD (billion m^3)	1.61	0.88	0.31
	Assurance probability of WDD (%)	80.86	89.74	96.06
	Mean annual WD (billion m^3)	6.69	7.56	8.72
	Lack of mean annual WD (billion m^3)	3.01	2.14	0.98
	Mean annual PG (billion kW h)	3.97	3.75	3.58
	Mean annual WVPG (billion m^3)	25.57	23.92	22.49
	Mean annual EWD (billion m^3)	15.30	11.97	8.57
	Lack of mean annual EWD (billion m^3)	0.10	0.04	0.04
	Assurance probability of EF (%)	98.53	99.31	99.85
2080s	Mean annual WDD (billion m^3)	11.01	11.43	11.65
	Lack of mean annual WDD (billion m^3)	0.76	0.35	0.12
	Assurance probability of WDD (%)	92.28	96.30	98.46
	Mean annual WD (billion m^3)	7.94	8.95	9.90
	Lack of mean annual WD (billion m^3)	1.76	0.75	0.00
	Mean annual PG (billion kW h)	4.59	4.31	4.14
	Mean annual WVPG (billion m^3)	28.33	26.18	24.82
	Mean annual EWD (billion m^3)	20.05	20.13	11.45
	Lack of mean annual EWD (billion m^3)	0.45	0.33	0.00
	Assurance probability of EF (%)	98.23	99.58	100.00

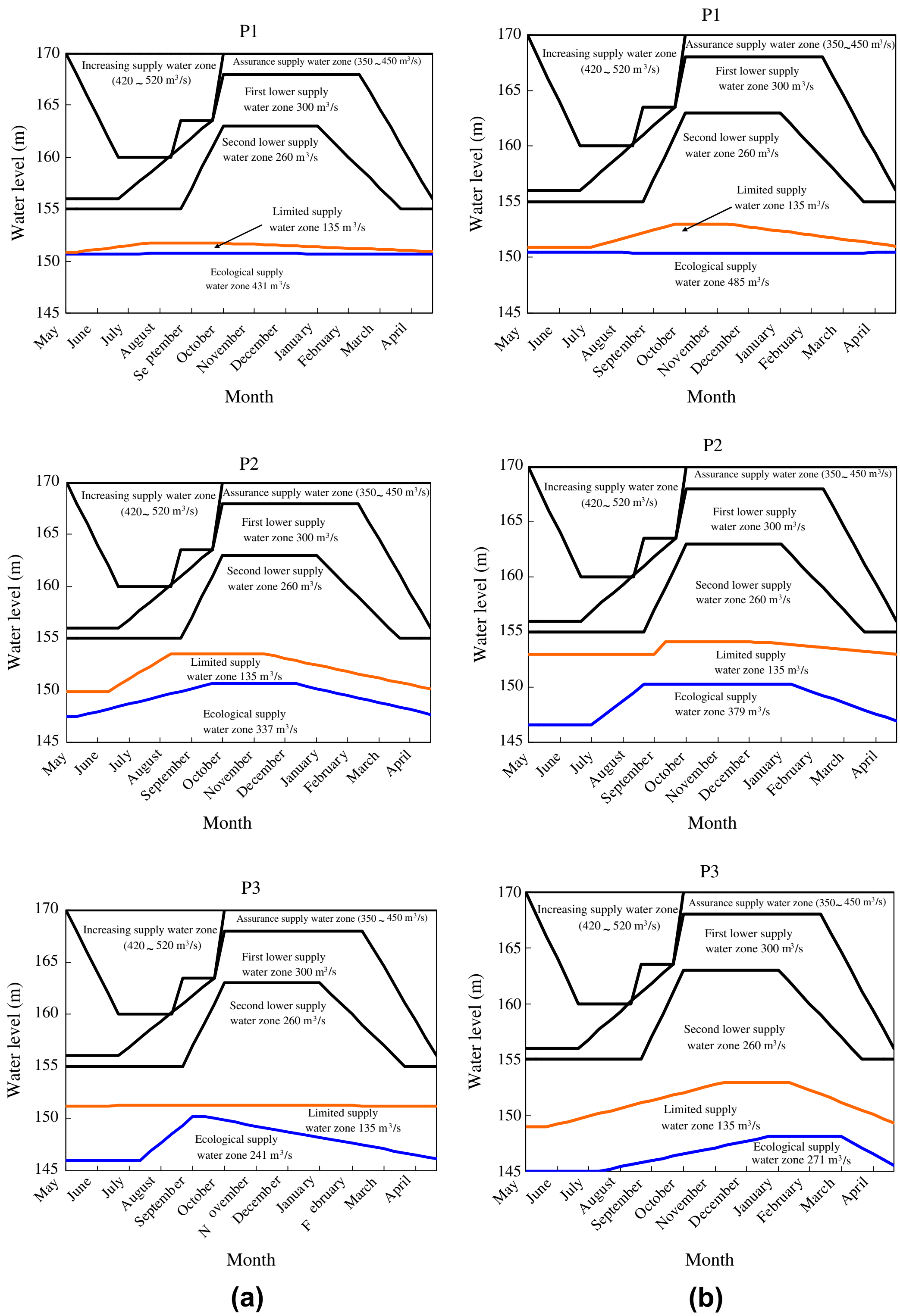


Fig. 6. Optimal operating rule curves of different ecological flow schemes in 2020s, 2050s, and 2080s. (a) 2020s. (b) 2050s. (c) 2080s.

(1) Only limited supply water curve and ecological supply water curve in Fig. 3 are selected as optimal operating rule curves. The differences among reservoir releases are insignificant because the reservoir often operates in high water level under the inflow of wet year.

(2) In contrast, the differences among reservoir releases are significant because the reservoir often operates in normal or dead water level under the inflows of normal and dry years. Especially, WDD, WD and GP are decreased in order to satisfy EWD in dry year.

3.2.3. Climate input

The validated SSVM downscaling model is used the model to downscale the future climate change scenario simulated by GCMs. This means that the large-scale predictor variables derived from A2 scenario of CGCM2 is used as input of SSVM downscaling model. Daily precipitation, daily mean, maximum and minimum temperatures are downscaled by SSVM for following three future periods, namely 2020s (2011–2040), 2050s (2041–2070) and 2080s (2071–2100). The downscaled precipitation and temperature data are input of VIC distributed hydrological model to simulate the annual runoff corresponding to future climate change scenario in the Han River basin (Guo et al., 2009). The simulated results of some hydrological stations are summarized in Table 3. Table 3 lists the relative changes of mean annual run-off in some hydrological stations. For example, under A2 scenario, the mean annual changes of runoff in Danjiangkou hydrological station will be about −16.69%, −1.27%, and 33.43% for the 2020s, 2050s, and 2080s, respectively.

3.2.4. Optimization of multipurpose operating rule curves under IAOM

The EFs corresponding to future climate change scenario are estimated using Tennant method with the simulated inflows in 2020s, 2050s and 2080s, and time interval is 10 days. The EFs of future climate change scenario are regarded as the minimum water discharge constrain for Danjiangkou reservoir.

The runoff (the time interval is 10 days) of VIC distributed hydrological model are input of DORCS and OORCS in current years to simulate conservation corresponding to future climate change scenario in the Danjiangkou reservoir. The simulated results of different EF schemes are summarized in Table 4. The optimal results of IAOM corresponding to future climate change scenario are summarized in Table 5. The optimal operating rule curves of IAOM corresponding to future climate change scenario are shown in Fig. 6.

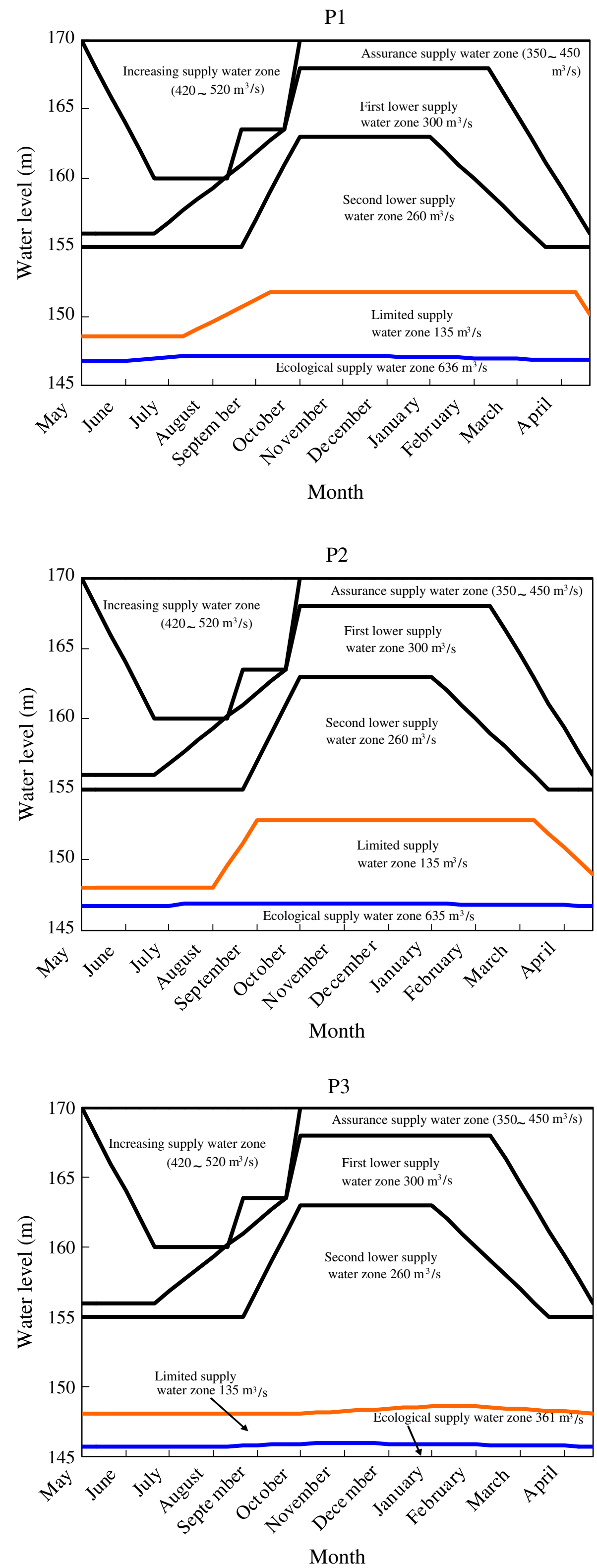
Table 4 shows that under A2 scenario, variation tendency of operation results for three future periods with DORCS and OORCS in current years is consistent with variation tendency of mean annual runoff for future three periods. Variation tendency of mean annual WDD, WD, EWD and PG for three future periods firstly decreases and then increases. Especially, operation results in 2050s are close to those in current years because mean annual runoff between them is similar. Evaluation criterion in OORCS is superior to that in DORCS. OORCS can averagely increase 0.941 billion m^3, 0.509 billion m^3, 0.633 billion m^3 and 0.045 kW h more mean annual WDD, WD, EWD and PG than DORCS for future periods among the schemes P1, P2, and P3, respectively. Besides, assurance probabilities of WDD and EF in OORCS averagely increase 3.88 and 1.72 among the schemes P1, P2, and P3, respectively, compared to DORCS.

The difference between the simulated results of OORCS in Table 4 and the optimal results of IAOM in Table 5 is very apparent. IAOM can averagely increase 0.493 billion m^3, 0.135 billion m^3, 0.082 billion m^3 and 0.200 kW h more mean annual WDD, WD, EWD and PG than OORCS for future periods among the schemes P1, P2, and P3, respectively. Besides, assurance probabilities of WDD and EF in IAOM averagely increase 2.16 and 0.99 among the schemes P1, P2, and P3, respectively, compared to OORCS.

Therefore, adaptability of IAOM is better than that of OORCS for climate change. However, adaptability of OORCS is better than that of DORCS for climate change.

Fig. 6 shows that the average height of limited supply water line and ecological supply water line increases firstly and then decreases in future three periods. The reasons are explained as follows:

(1) In order to improve the water utilization rate, the reservoir usually operates at a high water level and decreases the height of limited supply water line and ecological supply water line with the condition of wet years in 2080s.



(c)

Fig. 6 (*continued*)

(2) In order to firstly satisfy EWD, the reservoir usually operates at a lower water level and increases the height of limited supply water line and ecological supply water line with the condition of dry years in 2020s.

Besides, the shape of limited supply water curve and ecological supply water curve in 2020s is very similar to that of limited supply water line and ecological supply water line in current years because mean annual runoff between them is similar.

4. Discussions and conclusions

Decisions based on reservoir operating rule curves are vital important for seasonally balanced water supplies and the protection of reservoir downstream from ecological system or flooding in Han River basin. Global warming may bring more uncertain change in air temperature and precipitation which closely influence the hydrological process and ecological system. Ecological requirement of riverine ecosystem and future climate change should be taken into account when the operating rule curves are derived for multipurpose reservoir. In order to investigate the potential impact of climate change on the hydrological process, ecological system, and water resources in the region, this study incorporates ecological requirement into multipurpose reservoir operating rule curves employing a framework of the IAOM that consists of three modules: (1) GCM weather generator module, (2) VIC model as the hydrological simulation module, (3) multipurpose reservoir optimization module. As a result, under A2 scenario, the mean annual changes of runoff in Danjiangkou hydrological station will be about −16.69%, −1.27%, and 33.43% for the 2020s, 2050s, and 2080s, respectively. IAOM can generate extra 9.84 billion m^3 mean annual WDD (or increase 9.92%), 6.43 billion m^3 mean annual WD (or increase 8.87%), 2.44 billion kW h mean annual PG (or increase 6.72%) and 7.15 billion m^3 mean annual EWD (or increase 5.70%) than those of DORCS, respectively, for future 90 years in the Danjiangkou reservoir. The average height of limited supply water line and ecological supply water line increases firstly and then decreases in future three periods. The reasons are explained that the reservoir usually operates at a high water level and decreases the height of limited supply water line and ecological supply water line with the condition of wet years in 2080s in order to improve the water utilization rate, however, the reservoir usually operates at a lower water level and increases the height of limited supply water line and ecological supply water line with the condition of dry years in 2020s in order to firstly satisfy EWD. Besides, the shape of limited supply water curve and ecological supply water curve in 2020s is very similar to that of limited supply water line and ecological supply water line in current years because mean annual runoff between them is similar. Ecological supply water operation will alleviate negative effect of dam on river ecosystem without reducing conservation benefits and flood control standard.

Therefore, multipurpose reservoir operating rule curves good for most future conditions considered may be provided. Besides, further work will focus on extending the adaptation operating rule curves of single reservoir for cascade reservoirs or mixed multi-reservoir systems.

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