

Reservoir optimization model incorporating inflow forecasts with various lead times as hydrologic state variables

Tang Guolei, Zhou Huicheng and Li Ningning

ABSTRACT

This paper presents two Stochastic Dynamic Programming models (SDP) to investigate the potential value of inflow forecasts with various lead times in hydropower generation. The proposed SDP frameworks generate hydropower operating policies for the Ertan hydropower station, China. The objective function maximizes the total hydropower generation with the firm capacity committed for the system. The two proposed SDP-derived operating policies are simulated using historical inflows, as well as inflow forecasts with various lead times. Four performance indicators are chosen to assist in selecting the best reservoir operating policy: mean annual hydropower production, Nash–Sutcliffe sufficiency score, reliability and vulnerability. Performances of the proposed SDP-derived policies are compared with those of other existing policies. The simulation results demonstrate that including inflow forecasts with various lead times is beneficial to the Ertan hydropower generation, and the chosen operating policy cannot only yield higher hydropower production, but also produces reasonable storage hydrographs effectively.

Key words | hydropower operation, inflow forecasts with various lead times, quantitative precipitation forecasts, stochastic dynamic programming

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INTRODUCTION

Hydropower operation can be represented mathematically as a stochastic, nonlinear optimization problem, as future inflows and energy demands are uncertain and the system dynamics are nonlinear (Kim & Palmer 1997). Despite intensive research since the classic work of Young (1967), no generally applicable methods exist for solving reservoir operation problems. Rather, the choice of methods depends upon the characteristics of the reservoir system being considered and the specific objectives and constraints to be modeled (Yeh 1985). Since dynamic programming (DP) was first introduced (Bellman 1957), it has been recognized as a powerful technique for optimizing reservoir operation problems. Stochastic DP (SDP) is particularly well suited to

stochastic, nonlinear problems that characterize a large number of hydropower systems.

When applied to reservoir operation problems, SDP generates optimal releases that are a function of the system state variables, such as the beginning storage and hydrologic state variables. In SDP, the hydrologic state variables translate various hydrologic information into the required probabilistic framework. In general, the more hydrologic state variables used in an SDP, the better it can describe the stochastic nature of the inflows (Tejada-Guibert *et al.* 1995). Although several options for the hydrologic state variables are available, the most common choice is the current or previous period's inflow (Stedinger *et al.* 1984).

Many researchers have compared these two choices and the results depend on the specifics of the system under study. Several studies have ambitiously employed a monthly or seasonal flow forecast as a secondary choice of the hydrologic state variables (Kelman *et al.* 1990; Karamouz & Vasiliadis 1992; Tejada-Guibert *et al.* 1995). Tejada-Guibert *et al.* (1995) compared the performance of SDP models with different state variables for three different objectives to investigate the value of hydrologic information in SDP models. They found little difference between SDP models that employed different hydrologic state variables with an objective function stressing only energy maximization.

The significance of forecast uncertainty has seldom been considered in SDP models, although system performance may be significantly affected by the degree of uncertainty in forecasts (Kim & Palmer 1997). Stedinger *et al.* (1984) developed an SDP model, which employed the best forecast of the current period's inflow to define a reservoir release policy and to calculate the expected benefits from future operations. Karamouz & Vasiliadis (1992) proposed a Bayesian SDP (BSDP) incorporating a Bayesian approach within the SDP formulation. They stressed that flow transition probabilities from one month to the next can be updated as new forecasts become available. Such updating can significantly reduce the effects of natural and forecast uncertainties in SDP. Wang (2008) presents a hybrid SDP model (denoted by HSDP-1), that employs generated forecasts of inflow time series $\{Q_1^f, Q_2^f, \dots, Q_{t'}^f\}$ during the dry season and a discrete lag-one Markov process during the wet season as hydrologic state variables for the Ertan hydropower station, China. The simulation results demonstrate that including forecasts of inflow time series is beneficial by comparing the standard operating policy (SOP, Wang 2008).

Revisiting the Ertan reservoir operation problem, one-ten-day-ahead forecasts can be calculated by hydrologic models during the wet season, using Quantitative Precipitation Forecasts (QPFs) over the forthcoming 10-day periods as input, as medium-range QPFs show higher reliability in recent years (Collischonn *et al.* 2007; Yang *et al.* 2007). Therefore, the original Markov-typed inflow process for the wet season can be updated as one-ten-day-ahead forecasts become available. For these

situations, inflow forecasts with various lead times can be appropriate hydrologic state variables, integrating forecasts of inflow time series $\{Q_1^f, Q_2^f, \dots, Q_{t'}^f\}$ during the dry season, with inflow forecasts with one-ten-day lead time, $Q_{t'}^f$, during the wet season.

In this study, inflow forecasts with various lead times are incorporated as the second hydrologic state variable into two proposed SDP models, which are different from other SDP models. The SDP-derived operating policies are then simulated using a 48-year historical inflow and forecast series. Four performance indicators are chosen to assist in selecting the best reservoir operating policy: mean annual hydropower production, Nash-Sutcliffe sufficiency score, reliability and vulnerability. The performances of both proposed SDP-derived policies are evaluated by comparing the proposed SDP models with other existing models to examine the value of using the inflow forecasts with various lead times in SDP.

CASE STUDY SITE AND INFLOW FORECASTING

The case study site is the Ertan hydropower station, located in the lower reaches of the Yalong river basin in Sichuan Province, China. The study area has two distinct seasons, dry season (from November to April) and wet season (from May to October). A significantly large inflow usually occurs during the wet season because of the intensive heavy rainfall that is more than approximately 90% of the annual rainfall. The Ertan hydropower station is one of the key power sources for the Sichuan electric network with an annual hydropower generation of 16 880 GWh. Therefore Ertan operating policy is maximizing the total hydropower production. However, it is necessary to produce a firm capacity of 1,028 MW as far as possible to guarantee stable running of the system and peak-load regulation, especially during the dry season, when there is less rain. So the designed reliability probability of hydropower generation of the Ertan reservoir, defined as the probability of the system's output being satisfactory, is given as 95%, which is the ratio of the number of periods the system output is satisfactory and the total number of running periods during the years of operation (Hashimoto *et al.* 1982). More features are shown in Table 1.

Table 1 | Key descriptions of the Ertan hydropower station

Characteristic	Unit	Parameter
Dead storage capacity	Mm ³	2,430
Dead pool level	m	1,155
Gross storage capacity	Mm ³	5,800
Normal pool level	m	1,200
Usable storage capacity	Mm ³	3,370
Turbine capacity	m ³ /s	2,400
Plant capability	MW	3,300
Firm capacity	MW	1,208
Minimum release	m ³ /s	20
Power coefficient	-	8.6

The forecasts of Ertan reservoir inflow time series for the dry and wet seasons are modeled separately. For the dry season, monthly inflow time series is simulated using an Auto-Regressive Moving Average model (ARMA, Salas et al. 1980). For the wet season, a wavelet predictor-corrector model based on wavelet decomposition (WPC, Zhou et al. 2008) is used for 10-day inflow time series. The mean of the absolute relative error (MRE) and the Nash-Sutcliffe sufficiency score (NSSS) are the statistical parameters used to describe the accuracy of forecasting (Zhou et al. 2008). For a good prediction, MRE should be small and NSSS should be closer to 1. The statistics of MRE and NSSS are presented in Table 2. From the statistics of ARMA forecasting, it can be inferred that this model can be considered as an acceptable one for the dry season with MRE and NSSS at 4.6% and 0.99, respectively. However, WPC is not satisfactory for station level inflow forecasting for the wet season, as MRE and NSSS are obtained as 41.2% and 0.54, respectively. So the forecasts of inflow time series using the ARMA model can be appropriate hydrologic state variables during the dry season.

Although accurate forecasts of inflow time series are not generated during the wet season, it is still possible

Table 2 | Statistics of inflow time series forecasting for dry and wet seasons

Forecasting model	Training		Testing	
	MRE (%)	NSSS	MRE (%)	NSSS
ARMA	4.6	5.2	0.99	0.97
WPC	41.2	44.6	0.54	0.46

Table 3 | Statistics of real-time inflow forecasting models for the first 10 days of May

Forecasting model	Training			Testing		
	RMSE	CC	PP	RMSE	CC	PP
GRR	703	0.79	0.12	542	0.80	0.09
ANN	778	0.74	0.14	738	0.73	0.12

to obtain one-ten-day-ahead forecasts. In this study, the one-ten-day-ahead forecasts of inflows into Ertan dam are all obtained using a simple rainfall-runoff model with the QPFs from the Global Forecast System (GRR), run by the American National Oceanic and Atmospheric Administration. (Collischonn et al. 2007; Yang et al. 2007). The results are also compared with forecasts obtained by a Back-Propagation Artificial Neural Network model (ANN) currently in use. The Root Mean Square Error (RMSE), the Correlation Coefficient (CC) and the Performance Parameter (PP, the ratio of mean square error, MSE, and the variance of the observed values) are the statistical parameters (Sahai et al. 2000) used to describe the accuracy of forecasting. For a good prediction, RMSE should be small, CC should be closer to 1 and PP should be near to zero. The statistics RMSE, CC and PP are presented in Table 3, showing that the GRR model performs better than the ANN model in all cases. The reduction of RMSE is about 10% and the improvement in other statistics is similar. So the one-ten-day-ahead forecasts using the GRR model during the wet season can also be an appropriate hydrologic state variable.

Finally, inflow forecasts with various lead times F_t^S become available as described in Figure 1. The model is generalized by integrating forecasts of inflow series of a t^* month lead times $\{F_1, F_2, \dots, F_{t^*}\}$ (line AB), with inflow forecasts of only one-ten-day lead time F_t (line BC), where t is the index of the time period, t^* is the lead time of the forecasted inflow time series $\{F_1, F_2, \dots, F_{t^*}\}$; T is the number of all time periods and n is the number of time periods remaining until the end of the planning horizon.

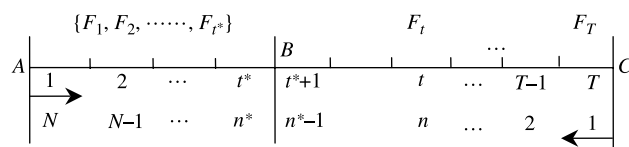


Figure 1 | Diagram of inflow forecasts with various lead times.

ALTERNATIVE SDP OPTIMIZATION MODELS

Classic stochastic dynamic programming

In classical SDP models, the optimal end storage S_{t+1} for time period t can be determined by solving the following recursive Equation (Tejada-Guibert et al. 1995):

$$f_{\text{opt}}^n(S_t, H_t) = E_{Q_t|H_t} \left(\text{Max}_{S_{t+1}} \left\{ B_t(S_t, Q_t, S_{t+1}) + E_{H_{t+1}|H_t, Q_t} \left\{ f_{\text{opt}}^{n-1}(S_{t+1}, Q_{t+1}) \right\} \right\} \right), \quad (1)$$

where S_t is the beginning storage for time period t , S_{t+1} is the target end storage for period t , Q_t is the inflow during period t , H_t is the hydrologic state variable for period t , $B_t(\cdot)$ is the immediate hydropower production from system operation during period t , $f_{\text{opt}}^n(\cdot)$ is the expected hydropower production from the current period to the end of the planning horizon and $E_{Q_t|H_t}$ is the conditional expectation operator for a flow of Q_t during period t , given a specific hydrologic state variable H_t .

Bayesian stochastic dynamic programming

BSDP, a term coined by Karamouz & Vasiliadis (1992), couples Bayesian estimation into an SDP framework. It can use inflow forecasts as well as the current month's inflow as the hydrologic state variables. When the current inflow Q_t and the monthly flow forecast F_t are used as the hydrologic state variables H_t through all periods, Equation (1) becomes (Karamouz & Vasiliadis 1992; Mujumdar & Nirmala 2007)

$$\begin{aligned} f_{\text{opt}}^n(S_t, Q_t, F_{t+1}) &= E_{Q_t|Q_t, F_{t+1}} \left(\text{Max}_{S_{t+1}} \left\{ B_t(S_t, Q_t, S_{t+1}) + E_{Q_{t+1}, F_{t+2}|Q_t, F_{t+1}, Q_t} \left[f_{\text{opt}}^{n-1}(S_{t+1}, Q_{t+1}, F_{t+2}) \right] \right\} \right) \\ &= \text{Max}_{S_{t+1}} \left\{ B_t(S_t, Q_t, S_{t+1}) + \sum_{Q_{t+1}=j} P_{ikj}^t \left[\sum_{F_{t+2}=l} P_{jl}^{t+1} f_{\text{opt}}^{n-1}(S_{t+1}, Q_{t+1}, F_{t+2}) \right] \right\} \quad (2a) \end{aligned}$$

$$P_{ij}^t = P[Q_{t+1} = j | Q_t = i] \quad (2b)$$

$$P_{jk}^{t+1} = P[F_{t+1} = k | Q_{t+1} = j]. \quad (2c)$$

$$P_{ikj}^t = P[Q_{t+1} = j | F_{t+1} = k, Q_t = i] = \frac{P_{jk}^{t+1} \cdot P_{ij}^t}{\sum_{Q_{t+1}} P[F_{t+1} = k | Q_{t+1}] \cdot P[Q_{t+1} | Q_t = i]} \quad (2d)$$

$$P_{jl}^{t+1} = P[F_{t+2} = l | Q_{t+1} = j] = \sum_{Q_{t+2}} P[F_{t+2} = l | Q_{t+2}] \cdot P[Q_{t+2} | Q_{t+1} = j] \quad (2e)$$

where i is the class interval of inflow Q_t in time period t , k is the class interval of inflow forecast F_{t+1} in period $t+1$, j is the class intervals of inflow Q_{t+1} in period $t+1$, P_{ij}^t is the prior inflow transition probability, and known prior to receiving the forecast for inflow (Karamouz & Vasiliadis 1992), Equation (2b); P_{jk}^{t+1} is the likelihood probability, showing the accuracy of the forecasts, Equation (2c), P_{ikj}^t is the posterior inflow transition probability and derived by incorporating F_{t+1} into P_{ij}^t and P_{jk}^{t+1} using the Bayesian theorem (Mayer 1970), Equation (2d), and P_{jl}^{t+1} is the predictive probability, which predicts the uncertain forecast F_{t+2} for the time period $t+2$, from Q_{t+1} , determined from the Total Probability Theorem (Mayer 1970), Equation (2e).

As seen in Equation (3) in the BSDP model, the derived operating policy takes into account the posterior inflow transition probability P_{ikj}^t , and the predictive probability of forecasts P_{jl}^{t+1} . These two probabilities together handle the inflow uncertainty and forecast uncertainty.

Two proposed SDP models

The two proposed SDP-type models employ the previous period's inflow Q_{t-1} and forecasts with various lead times (F_t^s) as hydrologic state variables, which are different from other SDP models. When the accurate forecasts of inflow time series $\{F_1, F_2, \dots, F_{t^e}\}$ are available during the dry season, both proposed SDP functional equations becomes simpler than Equation (1) during the dry season, because it does not consider any stochasticity of streamflow processes as in classical Deterministic Dynamic Programming (DDP).

Equation (1) can be reduced to

$$f_{\text{opt}}^n(S_t, F_t) = \left(\text{Max}_{S_{t+1}} \left\{ B_t(S_t, F_t, S_{t+1}) + f_{\text{opt}}^{n-1}(S_{t+1}, F_{t+1}) \right\} \right). \quad (3)$$

When the one-ten-day-ahead forecasts are available during the wet season, the SDP functional equation becomes more complex than Equation (1), as the proposed SDP models could use the previous period's inflow Q_{t-1} or the one-ten-day-ahead forecast F_t , or a combination of both. Although the two proposed SDP models are both an extension of the SDP model, the way hydrologic state variables are dealt with is different for the wet season. The recursive equations during the wet season will be given for both proposed models in the following section.

The first proposed model, denoted HBSDP, includes both the previous period's inflow Q_{t-1} and the one-ten-day-ahead forecast F_t as hydrologic state variables during the wet season. BSDP (Tejada-Guibert *et al.* 1995) includes the current period's inflow Q_t and the monthly flow forecast F_t . That is the difference between HBSDP and BSDP. The recursive equation for HBSDP during the wet season, therefore, can be given from Equation (1):

$$f_{\text{opt}}^n(S_t, Q_{t-1}, F_t) = \text{Max}_{S_{t+1}} \left\{ \sum_{Q_t=j} P_{ikj}^{t-1} \cdot \left(B_t(S_t, Q_t, S_{t+1}) + \sum_{F_{t+1}=l} P_{jl}^t \cdot f_{\text{opt}}^{n-1}(S_{t+1}, Q_t, F_{t+1}) \right) \right\}. \quad (4)$$

The last proposed SDP model, denoted HSDP-2, includes one-ten-day-ahead forecasts F_t as hydrologic state variables. That is because it is assumed that the forecast F_t is acceptable to represent the inflow Q_t in the HSDP-2 model, and then the posterior flow transition probability matrix will get transformed to an identity matrix. So Equation (4) can be reduced to

$$f_{\text{opt}}^n(S_t, F_t) = \text{Max}_{S_{t+1}} \left\{ B_t(S_t, F_t) + \sum_{F_{t+1}=l} P_{jl}^t \cdot f_{\text{opt}}^{n-1}(S_{t+1}, F_{t+1}) \right\}. \quad (5)$$

Obviously, the HSDP model is simpler than HBSDP. In each case, the conditional expectation is evaluated with conditional probabilities including inflow and forecast

transition probabilities, as detailed in Equation (2b)–(2e) and the later subsection.

MODEL APPLICATION

Objective function

Ertan operating policy should not only maximize the total hydropower production, but also produce a firm capacity as far as possible, subject to flood rule curve restrictions, release constraints and other physical and technical constraints. So once the system's output is not satisfactory, that is to say the calculated hydropower generation $P_t(\cdot)$ in MW for period t is less than the firm capacity (1,028 MW), system performance should be "punished" as shown in Equation (6). Thus, the objective function of Ertan operation can be written as

$$\begin{aligned} \text{Max} &= E \left[\sum_{t=1}^T B_t(S_t, Q_t, S_{t+1}) \right] \\ &= E \left[\sum_{t=1}^T (P_t(S_t, Q_t, S_{t+1}) \cdot \Delta t \right. \\ &\quad \left. - \alpha \cdot \left\{ \max(1028 - P_t(S_t, Q_t, S_{t+1}), 0) \right\}^\beta \cdot \Delta t) \right] \quad (6) \end{aligned}$$

where $P_t(\cdot)$ is the immediate hydropower production in MW for time period t , α and β are the penalty factors, usually with $\alpha = 1$ and Δt is the time in seconds for decision interval t .

Release from the reservoir constraints:

$$R_{\min,t} \leq R_t \leq R_{\max,t} \quad \text{for all } t = 1, 2, \dots, T \quad (7)$$

where $R_{\min,t}$ is the water released for environment protection, that is $20 \text{ m}^3/\text{s}$ and $R_{\max,t}$ is maximum water released from reservoir in time period t .

Output of power station constraint:

$$P_{\min,t} \leq P_t \leq P_{\max,t} \quad \text{for all } t = 1, 2, \dots, T \quad (8)$$

where $P_{\min,t}$ and $P_{\max,t}$ (3,300 MW) are minimum and maximum output of power station in time period t , and is expressed as a nonlinear function of the output limit curve.

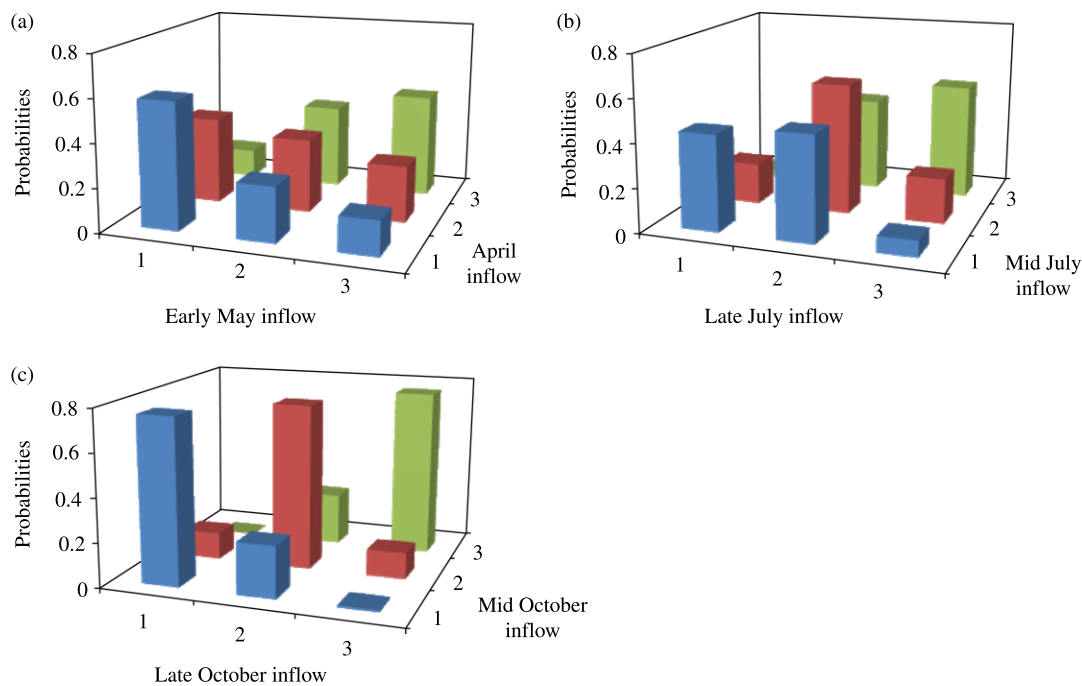


Figure 2 | Prior flow transition probabilities required in SDP-Q: (a) early May; (b) late July; (c) late October.

Turbine capacity constraint:

$$0 \leq RP_t \leq 2400 \text{ m}^3/\text{s} \quad \text{for all } t = 1, 2, \dots, T \quad (9)$$

where $2,400 \text{ m}^3/\text{s}$ is the total turbine capacity of the power plant.

Calculation of flow transition probabilities

To solve HSDP-2 and HBSDP, it is necessary to derive the conditional probabilities including prior transition probabilities and posterior transition probabilities by Equations (2b)–(2e). In many cases, it is computationally convenient to represent a state variable as a number of discrete values known as characteristic values such as characteristic storages and characteristic inflows (Karamouz & Vasiliadis 1992). The inflow and forecast are assumed to be log-normally distributed and then discretized with three characteristic values by using the nonuniform symmetric scheme in the Gaussian domain (Kim & Palmer 1997). Figure 2 shows prior flow transition probabilities for early May, late July and late October, when the lag-1 autocorrelation is low (0.41), medium (0.52) and high (0.89),

respectively. Because three characteristic inflows are used, the prior flow transition probability matrix contains nine probabilities for each period. In late October, the diagonal probabilities are large because of the high autocorrelation.

Figure 3 show the posterior flow transition probabilities used in HBSDP for all cases (low, medium and high) of the one-ten-day-ahead inflow forecasts obtained by the GRR model, for example, in early May and late October, respectively. The posterior flow transition probability matrix consists of nine probabilities for each characteristic forecast and each time period. In other words, the prior matrix for each time period is disaggregated into three posterior matrices according to the characteristic one-ten-day-ahead inflow forecasts (Kim & Palmer 1997). The posterior flow probabilities in early May are somewhat different from the corresponding prior flow transition probabilities although the correlations between the previous and current inflow are relatively weak. In late October, however, high correlations of the previous and current flows significantly affect the posterior probabilities and result in appreciable differences between the prior and posterior transition probabilities.

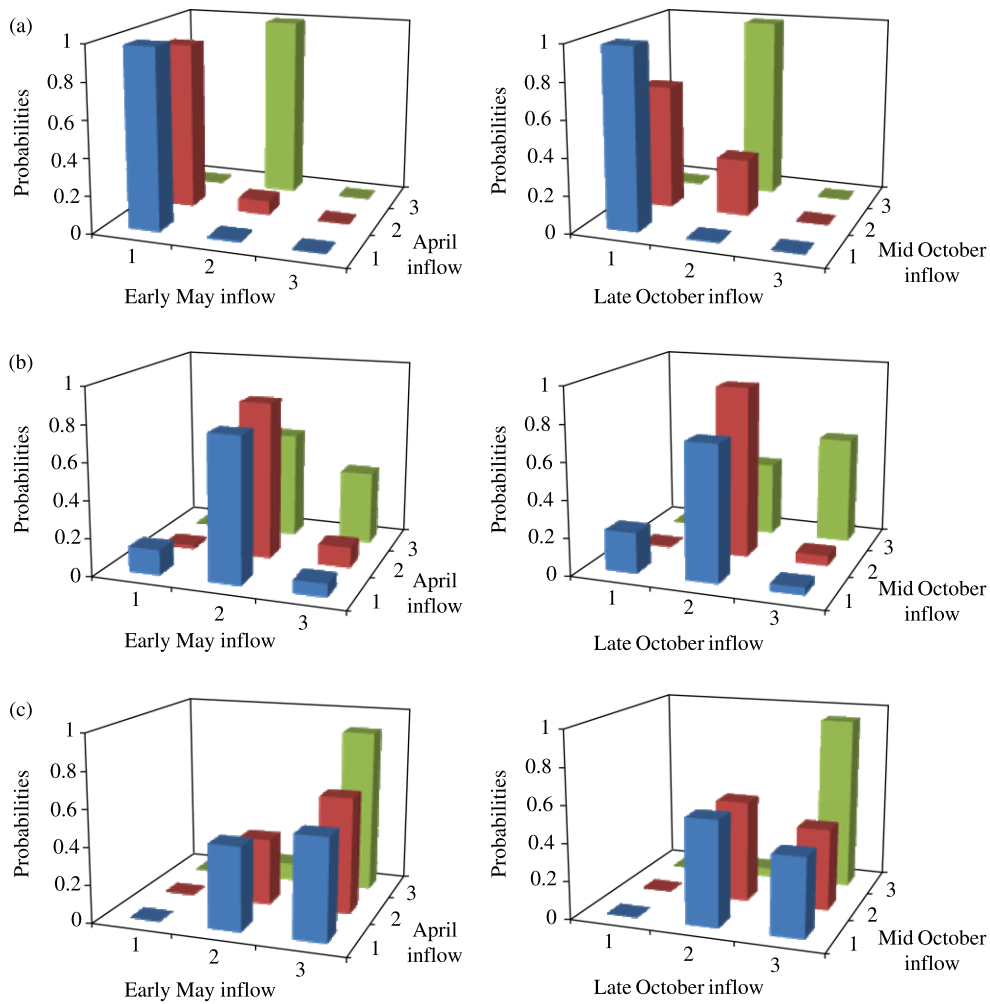


Figure 3 | Posterior flow transition probabilities for early May (left) and late October (right) using the predicted current inflows: (a) low, (b) medium and (c) high by GRR model.

Generation of steady-state operating policies

Using backward recursion, each SDP model is run iteratively until the end storages reach a steady state and the corresponding RPHG equals the Ertan designed RPHG as 95% by tuning the penalty factors α and β . So the generated operating policy for the Ertan reservoir is considered to be in the steady state when the expected average annual total power generation becomes constant for all periods and all combinations of the discretized state variables, and the obtained RPHG reaches 95%. Using these convergence criteria, HSDP-2 and HBSDP models using GRR forecasts as the hydrological state variable during the wet season, for example, require five and nine iterations, respectively, to generate the steady-state operating policy.

In this case, the Ertan beginning storage is discretized into 24 characteristic values using Savarenskiy's scheme (Klemes 1977). Figure 4 shows a typical HBSDP policy plot for early August derived by the proposed HBSDP model using GRR forecasts ($t = 15$, $\alpha = 1$ and $\beta = 2.5$). From the policy in Figure 4, the optimal Ertan end storage S_{16} can be obtained for a given combination of state variables including Ertan beginning storage S_{15} , Q_{14} and F_{15} , where Q_{14} here is the class interval of inflow during late July and F_{15} is the class interval of GRR inflow forecast during early August. Another policy plot of early August derived by the HSDP-2 model ($t = 5$, $\alpha = 1$ and $\beta = 2.0$) is also given in Figure 5. It is to arrive at values of S_{16} as a function of S_{15} and F_{15} .

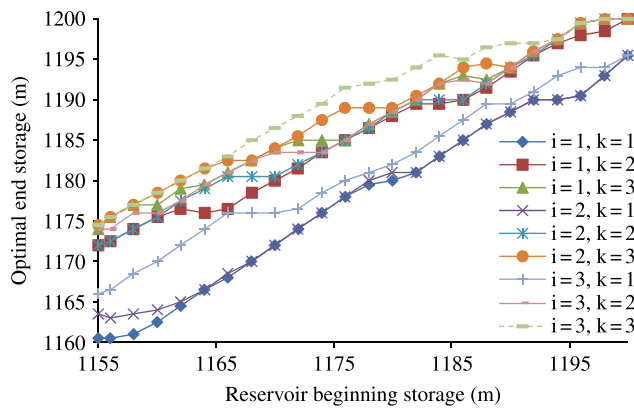


Figure 4 | A typical policy plot derived by the HBSDP model in early August for the Ertan reservoir.

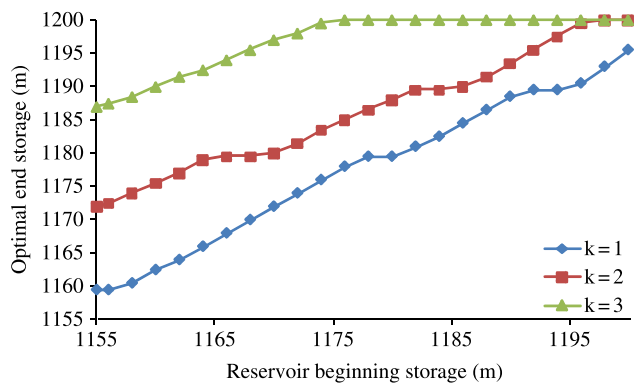


Figure 5 | A typical policy plot derived by the HSDP-2 model in early August for the Ertan reservoir.

Simulations of hydropower generation

The simulation analysis investigates the Ertan operation performance when the operating policies derived from the two proposed SDP models are employed in operation, using

a 48-year inflows and forecasts. Also the four performance indicators chosen to study the performances of the system under a given steady-state operating policy are: Mean Annual Hydropower Production (MAHP), NSSS, reliability and vulnerability. MAHP is the target value of optimization, so it is the most important one among these four indicators. NSSS is used here to measure how the storage hydrographs obtained by a given policy coincide well with the perfect storage hydrographs by DDP with historical inflow time series as input. The discussion about the last two indicators is taken from Vijaykumar et al. (1996) and Suresh (2002). Reliability of the system under a given policy is defined as the probability that the system output is satisfactory (Hashimoto et al. 1982). Vulnerability of the system under a given policy is defined as the ratio of the average of the largest deficit occurring in the year for the system to the firm power committed for the system, giving a measure of how large is the deficit.

Performance indicators are all listed in Table 4 for the derived HBSDP and HSDP-2 policies using GRR and ANN forecasts as hydrologic state variables during the wet season, respectively. To measure the value of incorporating inflow forecasts with various lead times as hydrologic state variables, this paper also gives simulations for standard operating policy (SOP) and HSDP-1-derived policy (Wang 2008), and their performance indicators are also listed in Table 4. The performance of the proposed SDP-derived policies should desirably result in high values for MAHP, NSSS and reliability and low values for vulnerability. At last, the performance indicators for DDP policy with perfect forecast time series are given in Figure 6, to explore the way how to further increase hydropower generation in the future.

Table 4 | Performance indicators for the all operating polices including SOP, HSDP-1, HBSDP and HSDP-2

Policy	Forecast modeling		Optimization model	MAHP (GWh)	Reliability (%)	NSSS	Vulnerability (%)
	Dry	Wet					
Existing polices	None	None	SOP	15,372	98.71	0.72	1.78
	ARMA		HSDP-1	16,758	95.15	0.79	4.45
ANN- HBSDP	ARMA	ANN	HBSDP	17,092	95.24	0.86	3.67
ANN-HSDP-2			HSDP-2	17,078	95.17	0.83	3.91
GRR- HBSDP	ARMA	GRR	HBSDP	17,106	95.12	0.92	2.59
GRR-HSDP-2			HSDP-2	17,108	95.11	0.93	2.63

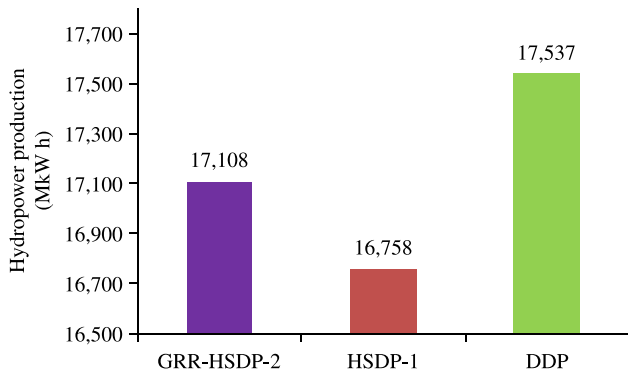


Figure 6 | The mean annual hydropower production by GRR-HSDP-2, HSDP-1 and DDP policies.

RESULTS AND DISCUSSION

The mean annual hydropower production is the most important indicator used to compare the proposed SDP policies with SOP and HSDP-1 policies. From the MAHPs in Table 4, it has been found that all these proposed derived policies using the forecasts with various lead times result in higher values of MAHP, approximately 338 MWh than HSDP-1 and 1,724 GWh than SOP policies on average. So incorporating inflow forecasts with various lead times is beneficial for the Ertan reservoir optimization, and the two proposed SDP models have also effectively improved the mean annual hydropower production by comparing the existing policies including HSDP-1 and SOP policies. Meanwhile, it is also concluded that the HSDP-2 policy is a little better than HBSDP when using GRR forecasts as hydrological state variables during the wet season; for the two proposed policies derived by using ANN forecasts, however,

the HBSDP policy is a better one than HSDP-2. The results show that the accuracy of inflow forecasts plays the governing role in selecting the optimization model. When the forecasts are acceptable, the prior flow transition probability matrix plays the governing role in the SDP algorithm, as in the GRR-HSDP-2 model. So the steady-state policy derived with an HSDP-2 model is used in situations where the satisfactory inflow forecasts could be gotten. When the forecasts are not perfect, i.e. forecast uncertainty exists, the likelihood matrix plays the governing role and, through Bayesian law, incorporates the forecast uncertainty in the optimization model, as in the ANN-HBSDP model. The steady-state policy derived with an HBSDP model may be used in situations where the forecasting skills are small due to impacts of climatic variability or due to a lack of adequate data. Finally, the GRR-HSDP-2 policy is chosen to optimize the Ertan reservoir operations in this study.

Also the higher values of reliability, NSSS and the lower value of vulnerability for both proposed derived policies are also acceptable for reservoir operation scheduling. Figures 7 and 8 give the storage hydrographs obtained using GRR-HSDP-2, HSDP-1 and DDP policies from 2003–2006. Obviously, the storage hydrographs obtained by HSDP-1 policy is not well matched with the perfect ones by DDP policies, and the optimal April end storages obtained from HSDP-1 are apparently higher than those from DDP. In 2003, for example, the optimal April end storage from HSDP-1 policy is 1181.5 m as shown in Figure 8, which is 15 m higher than 1166.5 m, the perfect April end storage by DDP. In contrast, the obtained storages and optimal April end storages by GRR-HSDP-2 policy are reasonable; they

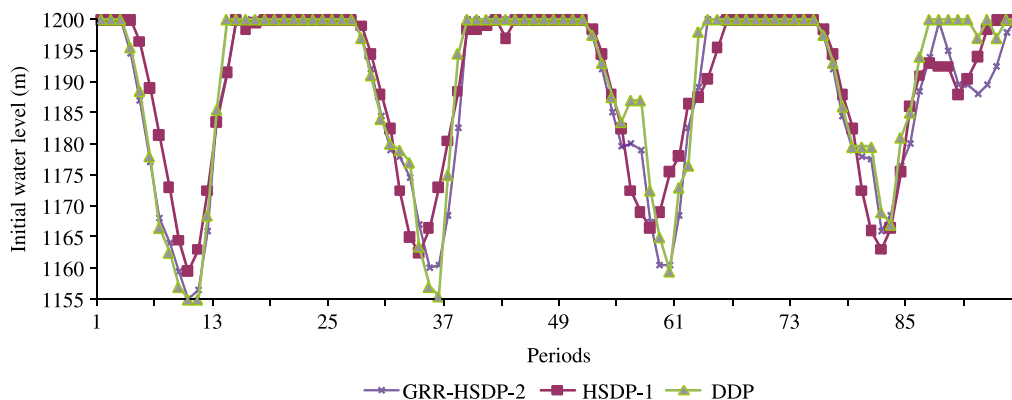


Figure 7 | Storage hydrograph obtained using GRR-HSDP-2, HSDP-1 and DDP policies from 2003 to 2006.

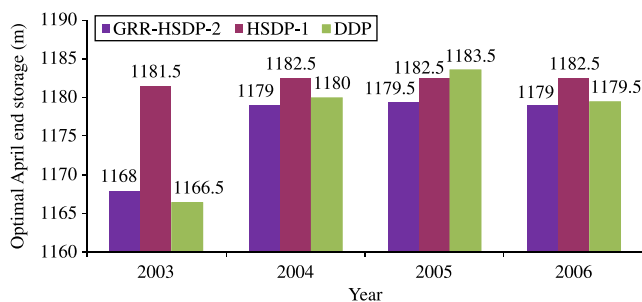


Figure 8 | The optimal April end storage by GRR-HSDP-2, HSDP-1 and DDP policies from 2003 to 2006.

are well matched with the perfect storages simulated by DDP, according to the values of NSSS for GRR-HSDP-2 policy obtained as 0.93, as illustrated in Table 4. This is due to the fact that HSDP-1 policy doesn't utilize any new forecasts during the wet season, which makes the optimal April end storages by HSDP-1 deviate from the perfect ones. The improvement on HSDP-1 policy demonstrates that including one-ten-day-ahead inflow forecasts during the wet season in the optimization model is beneficial for hydropower operation.

But it is worth noting that there is still 429 GWh of annual power production to be improved for GRR-HSDP-2 policy as compared to DDP policy as seen in Figure 6. DDP uses the perfect forecasts as hydrological state variables, so the posterior inflow transition probability and the forecast predictive probability matrix will get reduced to an identity matrix. Compared with DDP policy for the wet season, GRR-HSDP-2 policy takes into account the one-ten-day-ahead inflow forecasts using a GRR model, so the forecast predictive probability matrix is not an identity matrix, but determined by the prior inflow transition probability. In this case, the forecast lead time or the forecast predictive probability plays the governing role in the GRR-HSDP-2 model. To further increase the power generation, the forecast lead time has to be extended by making full use of available information on observer or predicted precipitation.

SUMMARY AND CONCLUSIONS

Two proposed SDP models including HSDP and HSDP-2 are presented to investigate the potential value of inflow forecasts with various lead times in hydropower

generation. In these optimization models, derived operating policy should not only maximize the total hydropower production, but also produce the firm capacity as far as possible, subject to flood rule curve restrictions, release constraints and other physical and technical constraints. These models for generating steady-state policy are presented using a single reservoir optimization problem and applied to an existing reservoir system, namely the Ertan reservoir in China.

Simulations of these proposed SDP-derived policies are carried out and compared with those existing policies including SOP and HSDP-1 policies. From these comparisons, it is observed that the accuracy of the inflow forecasting model plays the governing role in selecting the optimization model according to performance indicators: the operating policy derived with the HSDP model may be used in situations where the forecasting skills are small due to impacts of climatic variability or due to a lack of adequate data, and the steady-state policy derived with a HSDP-2 model is used in situations where the satisfactory inflow forecasts could be gotten.

Then, the corresponding GRR-HSDP-2 policy is chosen to optimize the Ertan reservoir operations in this study. The GRR-HSDP-2 policy cannot only effectively yield higher annual total hydropower generation, but also produces reasonable optimal end storage hydrographs which are well matched with the perfect ones by the deterministic dynamic programming model with historical inflow time series as input. Thus it can be concluded that incorporating inflow forecasts with various lead times is quite promising and very useful to derive efficient operating policies for a multi-reservoir system. Finally, it is concluded that it is necessary to extend the forecast lead time to further increase hydropower generation, by making full use of any available information on observer or predicted precipitation.

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