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수문학적 예측의 정확도에 따른 저수지 시스템 운영의 민감도 분석

Sensitivity Analysis for Operating a Reservoir System to Hydrologic Forecast Accuracy

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Abstract

This paper investigates the impact of the forecast error on performance of a reservoir system for hydropower production. Forecast error is measured as the Root Mean Square Error (RMSE) and parametrically varied within a Generalized Maintenance Of Variance Extension (GMOVE) procedure. A set of transition probabilities are calculated as a function of the RMSE of the GMOVE procedure and then incorporated into a Bayesian Stochastic Dynamic Programming model which derives monthly operating policies and assesses their performance. As a case study, the proposed methodology is applied to the Skagit Hydropower System (SHS) in Washington state. The results show that the system performance is a nonlinear function of RMSE and therefore suggested that continued improvements in the current forecast accuracy correspond to gradually greater increase in performance of the SHS.

Keywords: forecast accuracy, reservoir system operation, seasonal forecast, Bayesian stochastic dynamic programming

요 지

본 연구는 수력발전을 위한 저수지 관리에 있어 예측오차의 영향을 살펴보기 위해 예측오차를 Root Mean Square Error (RMSE)로 측정하였고, 이를 Generalized Maintenance Of Variance Extension (GMOVE) 기법을 통하여 변화시켜보았다. 변화된 예측오차의 RMSE는 천이확률을 통하여 Bayesian Stochastic Dynamic Programming (BSDP)에 고려되어졌으며, 이 BSDP 모형을 이용하여 월별 방류량을 결정하였고 그 유용성을 평가하였다. 제시된 연구방법은 미국의 Skagit 시스템에 적용되었고, 그 결과로 Skagit 시스템의 운영은 예측오차의 RMSE에 비선형이므로 반응하므로 이 시스템의 운영을 개선하기 위해서는 현재의 수문학적 예측기법을 개선해야함을 제시하였다.

핵심용어 : 예측 정확도, 저수지 시스템 운영, 계절별 예측, Bayesian 추계학적 동적계획법

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1. INTRODUCTION

The value of hydrologic forecast has been a topic of active research for a number of years, but few previous studies have attempted to assess system performance as a function of forecast accuracy. Yeh et al. (1982) and Mishalani and Palmer (1988) have used parametrically varied forecasts to investigate the impact of forecast uncertainty on reservoir operations. Their prediction coefficient that was used to vary the forecast accuracy in their studies, however, was not directly related to any measure of forecast error so that one could not translate a value of their prediction coefficient into a specific degree of the forecast accuracy. The prediction coefficient introduced by Lettenmaier (1984) explicitly represented the forecast accuracy but no attempt has been made to incorporate it into any reservoir system assessment.

This study derives a relationship between forecast accuracy and performance of a reservoir system. Seasonal flows are forecasted using a Multiple Linear Regression (MLR) model and the Root Mean Square Error (RMSE) of the MLR forecasts is calculated. This RMSE is parametrically reduced in the Generalized Maintenance Of Variance Extension (GMOVE) using a reduction factor. For each discrete value of the RMSE reduction factor, transition probabilities are estimated and incorporated into a reservoir operation model, Bayesian Stochastic Dynamic Programming (BSDP). The BSDP model derives monthly operating policies for the Skagit Hydropower System (SHS) in Washington state and estimate its Expected Annual Gain (EAG) as a performance criterion. As a result of this study, a plot of the EAG and the RMSE reduction factor is presented.

2. DESCRIPTION OF STUDY AREA

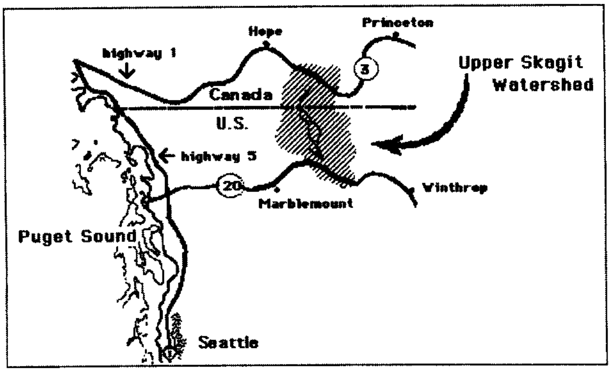
The SHS is located in the upper Skagit Valley of the North Cascade, approximately 140 miles north of Seattle (Figure 1). It produces a major portion of the electrical energy generated by Seattle City Light (SCL). The SHS consists of three hydropower dams, Ross, Diablo, and Gorge. Ross dam dominates the others in size with the total maximum capabilities of the Gorge, Diablo, and Ross plants being 176.7 MW, 159 MW, and 450 MW at maximum elevations, respectively (Seattle City Light, 1990). On a monthly basis, Diablo and Gorge are operated to maintain constant elevations, 875 ft and 1205 ft, respectively, while Ross varies between 1475 ft to 1602.5 ft. Therefore, the normal gross heads of the Diablo, and Gorge dams are 380 ft and 330 ft while the normal gross head of the Ross dam ranges from 270 ft to 397.5 ft.

Historical records for the natural inflows exist from July 1928 to the present, on monthly basis. For this study, data from January 1929 to December 1988 are used and assumed to be periodically stationary.

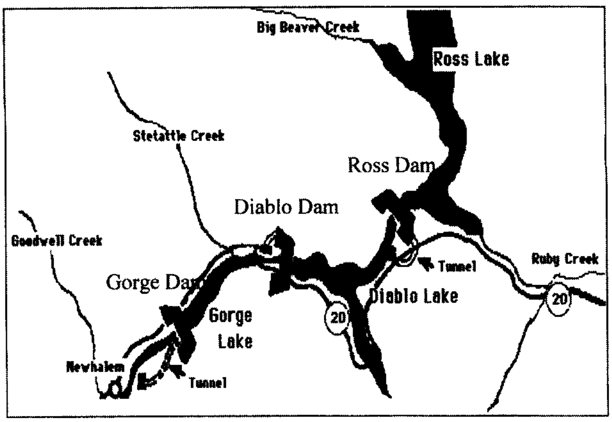
Like other rivers in the mountainous western United States where seasonal forecasts based on snow pack are particularly important in reservoir operations, more than 50 % of annual inflow into the SHS occurs from April through August. This hydrologic characteristic motivates use of seasonal forecasts during the snowmelt season when reservoir operating policies are derived. In this study, the seasonal flow is termed 'the through-August flow', defined by the remainder of the seasonal inflow through August (Kelman et al., 1990);

$$Y_t = \sum_{\tau=t}^{August} Q_\tau \qquad (1)$$

where Y_t is the through-August flow for month t and Q_t is the inflow during month t.



(a) Location of the Skagit Hydropower System.



(b) Details of the Skagit Hydropower System.

Figure 1. Map of the Skagit Hydropower System.

3. DEVELOPMENT OF SEASONAL FORECASTING MODEL

In many parts of the United States (US), the accuracy of seasonal forecasts is limited because such forecasts are highly dependent on precipitation, which in general, cannot be forecasted accurated for periods beyond several days (Lettenmaier and Garen, 1979). In mountainous areas such as the western US, seasonal flow forecasts are more accurate since a large portion of the spring and summer flow originates from winter precipitation that occurs as snow. During the snowmelt season (usually from April through August in the western US, there is relatively little precipitation, so the future runoff is more strongly affected by the snow accumulation at the beginning of the forecast period than by meteorological uncertainty. In this study, the through-August flows are forecasted using a MLR snowmelt runoff model and their accuracy is parametrically varied in the GMOVE procedure.

Development of a Snowmelt Runoff Model

Multiple linear regression models have been used widely for forecasting snowmelt runoff because they are simple and reasonably accurate for long-term forecasts (Hawley et al., 1980). To select an appropriate regression equation, it is necessary to select predictor variables based

Table 1. Regression Parameters, the Adjusted R^2 and the RMSE Associated with the Multiple Linear Regression.

Month	a_0^a	a_1^a	a_2^a	R^2 (%)	RMSE[b]
April	663.91	14.94	36.03	91	700.5
May	503.01	10.32	41.08	96	676.4
June	163.08	12.32	37.34	97	675.5
July	-211.42	13.81	25.67	91	1292.0

[a] regression parameters in equation (2), $F_t = a_0 + a_1PW_t + a_2W_t$, where PW_t and W_t are measured in inch and unit of F_t is cfs.

[b] RMSE associated with the multiple linear regression = $\sigma^*_{e_{t-1}}$ in equation (9).

on correlations of the snowmelt runoff with various hydrologic and meteorological series. The most common choices are total winter precipitation, runoff, and snow water equivalent (SWE), as noted by Grygier et al. (1989) for California river basins. Unlike California hydrology, however, the snowmelt runoff for the Skagit river basin can be best correlated with total winter precipitation and SWE. Thus, only two predictor variables are used in this study: total winter precipitation (PW_t) during the period from October to the date of forecast measured at Newhalem in Washington and average of SWEs measured at 15 snow courses at the date of forecast (W_t). At the beginning of a month, therefore, the through-August forecast (F_t) is calculated with the MLR equation,

$$F_t = a_0 + a_1PW_t + a_2W_t \tag{2}$$

The regression parameters for March, April, May and June are estimated in this study using the 37 years from 1952 through 1988 during which the SWE historical data are available. The least square estimates of the regression parameters are reported in Table 1. The adjusted R^2 in Table 1 indicates that the regression model explains more than 90 % of the variation in Ft for all the snowmelt months. The through-August flows are then forecasted for the same 37 years, assuming that the parameters are invariant year by year. Since the BSDP (which will be used as a reservoir operation model) requires 'one month ahead through-August forecast' (F_{t+1}), the current month's inflow is subtracted from the through-August forecast as follows:

$$F_{t+1} = F_t - Q_t \tag{3}$$

At the beginning of March, for example, the March-through-August forecast (F_t) is calculated using equation (2) to forecast the April-through-August flow. Hereafter, the seasonal forecast represents the one month ahead through-August forecast. The last column of Table 1 shows the RMSE of the MLR seasonal forecasts for each month. The values calculate the forecast accuracy associated with the MLR for the SHS and are parametrically reduced using the GMOVE procedure (that is described in the following section).

Parametrical Change of the Forecast Accuracy using the GMOVE

GMOVE has been developed as a record extension technique that can reproduce the forecast accuracy as well as the mean and variance of the existing forecasts (Grygier et al., 1989). In this study, the GMOVE is assumed to 'generate' a series of seasonal forecasts for a given value of the RMSE rather than to 'extend' the existing forecast series.

Consider the GMOVE equation that generates a seasonal forecast (F_{t+1}) using the current month's flow (Q_t) and the actual seasonal flow (Y_{t+1}):

$$F_{t+1} = \mu_{F_{t+1}} + b_t(Q_t - \mu_{Q_t}) + c_t(Y_{t+1} - \mu_{Y_{t+1}}) \tag{4}$$

where $\mu_{F_{t+1}}$ is the desired mean of the seasonal forecast series and $\mu_{Q_{t+1}}$ and $\mu_{Y_{t+1}}$ are sample estimates of mean of the current month's flow and the actual seasonal flow series, respectively. The coefficients b_t and c_t must satisfy:

$$b_t^2 = \frac{\sigma^2_{F_{t+1}} - \rho^2_{Y_{t+1}F_{t+1}}\sigma^2_{F_{t+1}}}{\sigma^2_{Q_t} - \rho^2_{Q_tY_{t+1}}\sigma^2_{Q_t}} \tag{5}$$

$$c_t = \frac{\rho_{Y_{t+1}F_{t+1}}\sigma_{F_{t+1}} - b\,\rho_{Q_tY_{t+1}}\sigma_{Q_t}}{\sigma_{Y_{t+1}}}$$

where $\sigma_{F_{t+1}}$ is the desired standard deviation of the forecast series, σ_{Q_t} and $\sigma_{Y_{t+1}}$ are sample estimates of standard deviation of the current month's flow and the actual seasonal flow series, respectively, $\rho_{Y_{t+1}F_{t+1}}$ is the desired correlation coefficient between the forecasts and the corresponding actual seasonal flows, and $\rho_{Q_tY_{t+1}}$ is a sample estimate of correlation coefficient between the current month's flows and the actual seasonal flows. Selection of the root of bt should maintain reasonable correlations of the seasonal forecasts with the current month's flows, as well as with the actual seasonal flows. For details, see Grygier et al. (1989).

In this study, GMOVE technique is assumed to be an unbiased forecast generator, i.e. $\mu_{F_{t+1}} = \mu_{Y_{t+1}}$. The statistics of the current month's flows and the actual seasonal flows (μ_{Q_t}, $\mu_{Y_{t+1}}$, σ_{Q_t}, $\sigma_{Y_{t+1}}$ and $\rho_{Y_{t+1}F_{t+1}}$) are estimated using monthly and seasonal historical data from January 1929 to December 1988. Generation of the forecasts using the GMOVE is then determined with only two parameters such as $\sigma_{F_{t+1}}$ and $\rho_{Y_{t+1}F_{t+1}}$ or equivalently the variance of the forecast error which satisfies:

$$\sigma^2_{e_{t+1}} = E[(Y_{t+1} - F_{t+1})^2] = \sigma^2_{Y_{t+1}} - 2\rho_{Y_{t+1}F_{t+1}}\sigma^2_{F_{t+1}}\sigma_{Y_{t+1}} + \sigma^2_{F_{t+1}} \tag{6}$$

The standard deviation of the forecasts is given from equation (6):

$$\sigma_{F_{t+1}} = \rho_{Y_{t+1}F_{t+1}}\sigma_{Y_{t+1}} \pm \sqrt{\sigma^2_{Y_{t+1}}(\rho^2_{Y_{t+1}F_{t+1}} - 1) + \sigma^2_{e_{t+1}}} \tag{7}$$

Since $\sigma^2_{Y_{t+1}}(\rho^2_{Y_{t+1}F_{t+1}} - 1) + \sigma^2_{e_{t+1}} \geq 0$, $\rho_{Y_{t+1}F_{t+1}}$ should be greater than its minimum correlation assuming that $\rho_{Y_{t+1}F_{t+1}}$ is positive,

$$\rho^{min}_{Y_{t+1}F_{t+1}} = \sqrt{1 - \left(\frac{\sigma_{e_{t+1}}}{\sigma_{Y+1}}\right)^2} \tag{8}$$

In this study $\rho_{Y_{t+1}F_{t+1}}$ is set to $\rho^{min}_{Y_{t+1}F_{t+1}}$ and thus the only variable required in the GMOVE procedure is $\sigma_{e_{t+1}}$ which is commonly known as the RMSE. To obtain various degrees of the forecast accuracy, the RMSE is parametrically varied using the following equation,

$$\sigma_{e_{t+1}} = (1 - \delta)\,\sigma^*_{e_{t+1}} \tag{9}$$

where $\sigma^*_{e_{t+1}}$ is the RMSE associated with the MLR (Table 1, last column) and δ is termed 'the RMSE reduction factor.' A smaller value of the RMSE results in a better prediction, reducing the variance of the seasonal forecasts and consequently narrowing the associated transition probability band.

For a given value of the reduction factor, GMOVE coefficients b_t and c_t can be calculated using equations (9), (7) and (5). Using the GMOVE coefficients, some correlations associated with the seasonal forecasts can be also derived as follows:

$$
\begin{aligned}
\rho_{Q_t F_{t+1}} &= \frac{b_t \sigma_{Q_t} + c_t \rho_{Q_t Y_{t+1}} \sigma_{Y_{t+1}}}{\sigma_{F_{t+1}}} \\
\rho_{Q_{t+1} F_{t+1}} &= \frac{b_t \rho_{Q_t Q_{t+1}} \sigma_{Q_t} + c_t \rho_{Q_{t+1} Y_{t+1}} \sigma_{Q_{t+1}}}{\sigma_{F_{t+1}}} \\
\rho_{F_t F_{t+1}} &= \frac{b_t^2 \rho_{Q_{t-1} Q_t} \sigma_{Q_{t-1}} \sigma_{Q_t} + b_t c_t \rho_{Q_t Y_t} \sigma_{Q_t} \sigma_{Y_t} + c_t^2 \rho_{Y_t Y_{t+1}} \sigma_{Y_t} \sigma_{Y_{t+1}}}{\sigma_{F_t} \sigma_{F_{t+1}}}
\end{aligned}
\qquad (10)
$$

Note that the lag-2 correlation between the monthly and seasonal flows are assumed to be negligible when $\rho_{F_t F_{t+1}}$ is derived. These correlations will be used to calculate transition probabilities required in the BSDP model which will be described in a later section.

4. DEVELOPMENT OF A RESERVOIR OPERATION MODEL

Kim and Palmer (1997) developed a BSDP model for operating the SHS to maximize the total benefit resulting from energy production of the SHS and its interchange with other systems. Coupling Bayesian estimation into a SDP framework, BSDP explicitly incorporates forecast uncertainties into the SDP formulation through the posterior flow transition probabilities. See Kim and Palmer (1997) for more detailed description of the prior and posterior transition probabilities as well as the BSDP equation. In this study, two hydrologic state variables are considered: the current months inflow and the seasonal forecast which represents one month ahead through August forecast as defined before. However, the current months inflow is used as the first hydrologic state variable for all months but the seasonal forecast is used as the second hydrologic state variable only for the snowmelt season from March through June.

The monthly operating rules derived by Kim and Palmer (1997) are assessed as a function of the forecast accuracy. To estimate the transition probabilities, the BSDP model basically requires four correlations: lag-1 autocorrelation of the monthly flows ($\rho_{Q_t Q_{t+1}}$), correlation of the current month's flows and the seasonal forecasts ($\rho_{Q_t F_{t+1}}$), correlation between the next month's flows and the seasonal forecasts ($\rho_{Q_{t+1} F_{t+1}}$), and the lag-1 autocorrelation of the seasonal forecasts ($\rho_{F_t F_{t+1}}$). The lag-1 autocorrelation of the monthly flows is estimated from the historical data while the other three correlations are estimated using equation (10).

5. STUDY RESULTS

As mentioned previously, the RMSE associated with the MLR is parametrically reduced uisng the reduction factor (δ) in equation (9). In this study, δ is increased by 0.1 from 0 which indicates the MLR to 1 which indicates the perfect forecasting technique. Table 2 presents the GMOVE coefficients (b_t and c_t) and the corresponding values of the minimum correlation ($\rho^{\min}_{Y_{t+1} F_{t+1}}$), the RMSE ($\sigma_{e_{t+1}}$), the variance of the seasonal forecast ($\sigma_{F_{t+1}}$), and the correlations of the seasonal forecasts described in equation (10) when the RMSE reduction factor is 0.5. Using each set of b_t, c_t, $\rho^{\min}_{Y_{t+1} F_{t+1}}$, $\sigma_{e_{t+1}}$, $\sigma_{F_{t+1}}$, $\rho_{Q_t F_{t+1}}$, $\rho_{Q_{t+1} F_{t+1}}$, $\rho_{F_t F_{t+1}}$, the transition probabilities are calculated so that the BSDP model derives the steady state monthly operating policies and predicts the EAG.

The EAG of the SHS for each value of the RMSE reduction factor is presented in Table 3 and Figure 2. From Table 3, it is found that use of the MLR forecasting technique (= 0) is expected to result in 2.8 million dollars a year

Table 2. The GMOVE coefficients[a] and the Relevant Statistics[b] for the Seasonal Forecast when the RMSE reduction factor = 0.5.

	March	April	May	June
b_t	-0.3205	-0.1959	-0.1364	-0.2476
c_t	0.9907	0.9568	1.0024	1.2214
$\rho^{min}_{Y_{t+1}F_{t+1}}$	0.9720	0.9828	0.9877	0.9300
$\sigma_{e_{t+1}}$	350.3	338.2	337.8	646.0
$\sigma_{F_{t+1}}$	1449.9	1797.6	2132.8	1634.0
$\rho_{Q_tF_{t+1}}$	-0.0386	-0.2334	0.0151	0.4168
$\rho_{Q_{t+1}F_{t+1}}$	0.0993	0.4241	0.9132	0.9131
$\rho_{F_tF_{t+1}}$		0.9113	0.9010	0.9283

[a] the GMOVE coefficients in equation (4), $F_{t+1} = \mu_{F_{t+1}} + b_t(Q_t - \mu_{Q_t}) + c_t(Y_{t+1} - \mu_{Y_{t+1}})$.

[b] the statistics defined in equations (7), (8), (9), and (10).

while the perfect forecasting technique (= 1) is expected to result in 8.9 million dollars a year. The maximum potential benefit associated with a better forecasting technique is significant, approximately 5.9 million dollars which is twice as large as the EAG of the MLR. For the SHS,

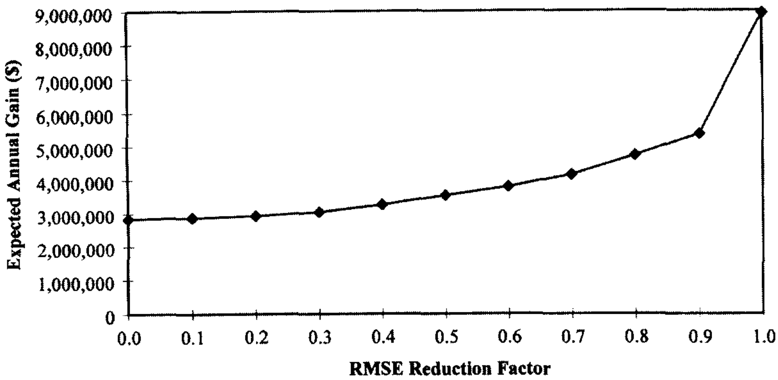


Figure 2. Relationship between the RMSE Reduction Factor and the Expected Annual Gain for the Skagit Hydropower System.

Table 3. The Expected Aunnal Gain (10^6 $) as a Function of the RMSE reduction Factor

δ [a]	0.0	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1.0
EAG[b]	2.843	2.874	2.928	3.040	3.261	3.538	3.794	4.155	4.736	5.37	8.94
Δ_{abs} [c]		0.03	0.05	0.11	0.22	0.28	0.26	0.36	0.58	0.64	3.56
Δ_{rel} [d]		1.10	1.88	3.84	7.27	8.48	7.22	9.51	14.00	13.42	66.34

[a] δ = the RMSE reduction factor in equation (9).

[b] EAG = the expected annual gain.

[c] $\Delta_{abs} = EAG_{k+1} - EAG_k$ and unit is 10^6 $.

[d] $\Delta_{rel} = (EAG_{k+1} - EAG_k)100/EAG_k$ where k is the k-th discrete value of δ and unit is %.

therefore, development of a better forecasting technique than the MLR may produce a large potential benefit.

A plot in Figure 2 shows nonlinear relationship between the reduction factor and the EAG. Because the slope of the curve can be interpreted as the incremental increase in the EAG associated with a unit improvement in the reduction factor, the convex feature of the curve suggests that continued improvements in the forecast accuracy (such as the RMSE) over the MLR forecasting technique corresponds to gradually greater increases in performance (such as the RMSE) of the SHS. In other words, as the forecast accuracy increases, the SHS becomes more sensitive to a unit improvement in the forecast accuracy.

6. CONCLUSIONS

In this study, an attempt is made to investigate a relationship between forecast accuracy and performance of a reservoir system. The forecast accuracy is measured as the RMSE and varied in the GMOVE procedure while the system performance is measure as the EAG and estimated by the BSDP model. From the experimental result for the SHS, the range of potential benefits associated with use of better forecasts than the MLR forecasts is found to be significant. A plot of the EAG versus the RMSE shows the convex curve which suggests continued improvements in the forecast accuracy over the MLR forecasting technique corresponds to gradually greater increases in performance of the SHS.

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