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Joint and respective effects of long- and short-term forecast uncertainties on reservoir operations

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SUMMARY

Forecast uncertainties are a major problem in forecast-based water resource management. This study aims to improve the combined use of long- and short-term streamflow forecasts in reservoir operations by investigating the joint and respective effects of long- and short-term forecast uncertainties on decision-making processes. Forecast uncertainties in ensemble streamflow forecasts are explained, and the joint effect is characterized by a matrix of operation decisions. A novel statistical partitioning method is developed to diagnose the respective effects of long- and short-term forecast uncertainties, particularly on an experimental operation of the Danjiangkou Reservoir in China. Given the large regulating capacity of this reservoir, long-term forecast uncertainties inevitably surround its release decisions. When a fixed carried-over storage is used to couple long- and short-term forecasts, an ending storage effect is observed. As a stage approaches its end, the release decision becomes increasingly dependent on the carried-over storage, thereby increasing uncertainty in decision-making as a result of long-term forecast uncertainty. This finding highlights the importance of developing reliable long-term forecasts and selecting a proper carried-over storage to aid the decision-making process. This study proposes a sliding carried-over storage strategy to circumvent the ending storage effect. Results show that, using the same long-term forecast, the proposed strategy significantly alleviates the ending storage effect and reduces uncertainties in the decision-making process. The sliding carried-over storage strategy provides an efficient approach to the combined use of long- and short-term forecasts and improves reservoir operations.

1. Introduction

Recent developments in hydrological modeling, weather forecasting, and hydro-climatic teleconnections have significantly improved streamflow forecasts (Maurer and Lettenmaier, 2003; Ajami et al., 2007; Georgakakos et al., 2012a). Advanced hydrological modeling and weather forecasting have particularly improved short-term streamflow forecasts. Explorations in hydro-climatic teleconnections, such as the statistical relationships between local streamflow and global climatic indices (e.g., El Niño Southern Oscillation and North Atlantic Oscillation), have particularly improved long-term streamflow forecasts. For example, operational forecasting systems utilize numerical weather predictions to drive hydrological models and to obtain short-term ensemble flood forecasts (Cloke and Pappenberger, 2009; Alfieri et al., 2013); machine learning models (e.g., neural networks and support vector machines), exploit teleconnection relationships, and produce long-term streamflow predictions (Maurer and Lettenmaier, 2003; Kalra et al., 2013). Short-term forecasts are reliable but have a limited forecast horizon ranging from several hours to a few days (Pianosi and Soncini-Sessa, 2009; Zhao et al., 2013; Galelli et al., 2014). By contrast, long-term forecasts have a long forecast horizon of several months, but are beset by large uncertainties (Sankarasubramanian et al., 2008; Georgakakos et al., 2012a).

In recent years, streamflow forecasts have been extensively applied in reservoir operations, including long-term scheduling and short-term decision-making (e.g., Maurer and Lettenmaier, 2004; Ajami et al., 2008; Georgakakos et al., 2012b). Given that streamflow forecasts provide more reliable information on future streamflow than historical streamflow sequences do, forecast-based decision-making yields more economic benefits than conventional operating rules do (Maurer and Lettenmaier, 2004; Sankarasubramanian et al., 2008; Georgakakos et al., 2012b). Streamflow forecasts offer a promising approach in enhancing the efficiency of the reservoir system. However, the use of streamflow forecasts is beset by forecast uncertainties that lead to profit losses and operational risks (Zhao et al., 2013, 2014). Many efforts have been devoted on developing optimization models that deal

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with decision-making processes surrounded by uncertainties (Labadie, 2004; Pianosi and Soncini-Sessa, 2009; Galelli et al., 2014).

Optimization models treat streamflow forecasts as the given input and output operation decisions (Labadie, 2004). In such process, optimization models function like black boxes that do not interpret the relationship between input forecast and output decision. Given the significance of forecast uncertainties, a theoretically interesting and practically important issue is their effects on decision-making. Identifying such effects not only helps to understand decision-making surrounded by uncertainties but also facilitates the efficient use of forecast information (Georgakakos, 1989; You and Cai, 2008; Graham and Georgakakos, 2010). Combining statistical models with optimization models, Maurer and Lettenmaier (2003, 2004) evaluated the effects of long-term forecast uncertainties and demonstrated an increase in hydropower profit from an improvement of long-term forecast. Zhao et al. (2011, 2013) analyzed the effects of short-term forecast uncertainties following Gaussian and non-Gaussian distributions.

Previous studies have analyzed the individual effects of long- and short-term forecast uncertainties and disregarded their joint effect. However, long- and short-term streamflow forecasts are usually used in combination in reservoir operations to take advantage of the long horizon of long-term forecasts and the high reliability of short-term forecasts (Alemu et al., 2011; Eum et al., 2011; Georgakakos et al., 2012b). Thus, the joint effect of long- and short-term forecast uncertainties is an important issue that is yet to be addressed. This study fills this research gap and presents a novel statistical method of diagnosing the joint and respective effects of long- and short-term forecast uncertainties on reservoir operations. The method is applied to an experimental operation of the Danjiangkou Reservoir in China. A new reservoir operation strategy with sliding carried-over storage is developed from the method. The remainder of the paper is organized as follows. Section 2 presents the formulations of coupling long- and short-term forecasts in reservoir operations. Section 3 introduces the novel statistical method. Section 4 describes the reservoir operation experimental setup that analyzes the joint and respective effects of forecast uncertainties. Section 5 draws some conclusions.

2. Formulation of forecast-based reservoir operations

Streamflow forecasts provide useful information on future streamflow and facilitate reservoir operations. Long-term forecasts are applied in long-term scheduling, such as the monthly planning of water supply, whereas short-term forecasts are used in short-term decision-making, such as determining the level of daily release. This section presents the details of formulating forecast-based reservoir operations.

2.1. Reservoir operation optimization

The framework of the combined use of long- and short-term forecasts in reservoir operations may be outlined as follows. (1) The operation horizon comprises the TL stages (e.g., an annual regulating reservoir has an operation horizon of 12 months), and each stage consists of TS time steps (e.g., one month includes approximately 30 days). Thus, the total operation horizon consists of $TL \times TS$ time steps. (2) Long-term forecasts provide streamflow information at each stage up to the end of the operation horizon and are updated stage by stage. (3) Short-term forecasts provide streamflow information with a forecast horizon of FH time steps and are periodically updated. An assumption here is that short-term forecasts provide streamflow information for one whole stage (i.e., $FH = TS$). Fig. 1 shows a schematic representation of the stages, time steps, and evolving forecasts in reservoir operations.

Before examining the details of forecast-based reservoir operations, a general reservoir optimization model is first considered

$$
\begin{aligned}
&\max \quad B = \sum_{t=1}^{T} b_t(s_t, q_t, r_t) \\
&s.t \quad \begin{cases} s_t + q_1\Delta - r_1\Delta = s_{t+1} \quad (t = 1, 2, \ldots, T) \\ \underline{s} \le s_t \le \bar{s} \quad (t = 2, 3, \ldots, T) \\ \underline{r} \le r_t \le \bar{r} \quad (t = 1, 2, \ldots, T) \\ s_1 = s_{ini} \\ s_{T+1} = s_{end} \end{cases}
\end{aligned}
\tag{1}
$$

In Eq. (1), t denotes the time index; s_t denotes the reservoir storage at the beginning of period t, whose lower and upper bounds are $\underline{s}$ and $\bar{s}$, respectively; q_t denotes the inflow during period t; r_t denotes the release in period t, which is bounded by $\underline{r}$ and $\bar{r}$; Δ denotes the period length and converts the unit of q_t and r_t (m^3/s) into that of s_t (m^3); and $b_t(s_t, q_t, r_t)$ denotes the utility function of period t (e.g., revenue function of water supply).

The objective is to maximize B, the sum of the utilities from periods 1 to T. The reservoir operation is subject to the three typical constraints of water balance, release capacity, and storage capacity (Labadie, 2004). The initial storage s_{ini} and ending storage s_{end} are given and set the boundary conditions for the reservoir operation (Kim et al., 2007; Alemu et al., 2011; Zhao et al., 2012a). The decision variable may either be $s_t (t = 2, 3, \ldots, T)$ or $r_t (t = 1, 2, \ldots, T)$; s_t (r_t) can be inferred from r_t (s_t) via the water balance. Eq. (1) disregards storage losses caused by evaporation and leakage in the water balance relationship, and circumvents the utility-to-go function (Bellman, 1957) (i.e., the value function of water saved for periods beyond T) by treating s_{end} as a fixed value.

To solve the optimization model Eq. (1) yields three important outputs. One output is the optimal storage decisions $s_t (t = 2, 3, \ldots, T)$, which represent the carried-over storage from periods preceding t to subsequent periods. The optimal storage decisions also indicate the trade-offs between the utilities in the preceding and subsequent periods of water allocation. Another output is the optimal release decisions $r_t (t = 1, 2, \ldots, T)$, which represent water resources that are allocated for period t and that contribute to single-period utility $b_t(s_t, q_t, r_t)$. The third output is the maximum total utility B, which indicates the efficiency of the reservoir system. The future streamflow $[q_1, q_2, \ldots q_T]$ is not known, and streamflow forecasts are applied to reservoir operations (Sankarasubramanian et al., 2008; Graham and Georgakakos, 2010; Zhao et al., 2012b).

2.2. Reservoir operation with fixed carried-over storage

By adding the superscript L to the variables in Eq. (1), we formulate the optimization model of long-term scheduling based on the long-term forecast $[f^L_{tl,tl} \quad f^L_{tl,tl+1} \quad \cdots \quad f^L_{tl,TL}]$ ($f^L_{tl,tl+i}$ denotes stage tl's forecast of stage $tl + i$'s streamflow)

$$
\begin{aligned}
&\max \quad B^L = \sum_{t=tl}^{TL} b^L_t(s^L_t, f^L_{tl,t}, r^L_t) \\
&s.t \quad \begin{cases} s^L_t + f^L_{tl,t}\Delta^L - r^L_t\Delta^L = s^L_{t+1} \quad (t = tl, tl+1, \ldots, TL) \\ \underline{s} \le s^L_t \le \bar{s} \quad (t = tl+1, \ldots, TL) \\ \underline{r} \le r^L_t \le \bar{r} \quad (t = tl, tl+1, \ldots, TL) \\ s^L_{tl} = s_{ini} \\ s^L_{TL+1} = s_{end} \end{cases}
\end{aligned}
\tag{2}
$$