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Forecast-skill-based simulation of streamflow forecasts

Tongtiegang Zhao, Jianshi Zhao *

State Key Laboratory of Hydro-Science and Engineering, Department of Hydraulic Engineering, Tsinghua University, Beijing, China

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ABSTRACT

Streamflow forecasts are updated periodically in real time, thereby facilitating forecast evolution. This study proposes a forecast-skill-based model of forecast evolution that is able to simulate dynamically updated streamflow forecasts. The proposed model applies stochastic models that deal with streamflow variability to generate streamflow scenarios, which represent cases without forecast skill of future streamflow. The model then employs a coefficient of prediction to determine forecast skill and to quantify the streamflow variability ratio explained by the forecast. By updating the coefficients of prediction periodically, the model efficiently captures the evolution of streamflow forecast. Simulated forecast uncertainty increases with increasing lead time; and simulated uncertainty during a specific future period decreases over time. We combine the statistical model with an optimization model and design a hypothetical case study of reservoir operation. The results indicate the significance of forecast skill in forecast-based reservoir operation. Shortage index reduces as forecast skill increases and ensemble forecast outperforms deterministic forecast at a similar forecast skill level. Moreover, an effective forecast horizon exists beyond which more forecast information does not contribute to reservoir operation and higher forecast skill results in longer effective forecast horizon. The results illustrate that the statistical model is efficient in simulating forecast evolution and facilitates analysis of forecast-based decision making.

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1. Introduction

Water resource system analysis faces the problem of unknown future streamflow [17,21,26]. Conventionally, future streamflow conditions are represented by streamflow variability and stochastic models are developed for synthetic streamflow generation. Streamflow sequences that contain statistical properties similar to those of historical streamflow data are generated and then applied to assist in water resource planning, e.g., reservoir capacity determination, storage yield analysis, and irrigation system design [15,18,25]. In recent years, streamflow forecasting has been improved considerably, which has provided useful information concerning future streamflow in real time. Meanwhile, streamflow forecasting has not yet been perfected and remains characterized by forecast uncertainty [11,23,34].

Streamflow variability and forecast uncertainty are two key issues in water resource studies [1,5,27]. Streamflow variability has been sufficiently addressed in stochastic hydrology. Parametric models (e.g., time series models) and nonparametric models (e.g., K-nearest neighbor models) are used in synthetic streamflow generation [6,30,33]. By contrast, only a few stochastic models are concerned with forecast uncertainty. Water resources studies illustrated that applications of streamflow forecasts lead to more economic benefits compared with conventional operating rules, which are considerably affected by forecast uncertainty [9,23,28]. Meanwhile, previous forecast-based decision making provides a limited number of samples, which causes difficulty in generalizing the relationship between economic benefit and forecast uncertainty. The use of stochastic models enables explicit characterization and simulation of forecast uncertainty and can bridge this gap [2,10,23]. Based on stochastic models that address streamflow variability, this study develops a stochastic model for simulating forecast uncertainty.

Combining stochastic models of forecast uncertainty with optimization models facilitates analysis of forecast-based decision making. For example, Maurer and Lettenmaier [22], Maurer and Lettenmaier [23] developed stochastic models of predictability and evaluated economic benefits from predictability of seasonal streamflow. Georgakakos and Graham [10] and Graham and Georgakakos [12] assessed the benefits of streamflow forecasts and illustrated that the use of forecast is affected by characteristics of reservoir systems. Zhao et al. [37,39] constructed models of the evolution of streamflow forecasts and evaluated the effects of

* Corresponding author. Tel.: +86 10 62796539; fax: +86 10 62796971.
E-mail address: zhaojianshi@tsinghua.edu.cn (J. Zhao).

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Gaussian and non-Gaussian forecast uncertainties on reservoir operation. These studies are based on parametric stochastic models for which the statistical distributions and a number of related parameters should be specified. Using parametric models, we develop a forecast-skill-based model of forecast evolution (FMFE) with three advantageous properties. First, the model is based on forecast skill, which is a key metric for forecast evaluation that can be derived from previous forecasts. Second, the model is nonparametric and does not involve tedious statistical specifications, e.g., mean, variance, and covariance. Third, the model takes full advantage of stochastic models, which are used in synthetic streamflow generation.

In the remainder of the paper, Section 2 presents a brief summary of the parametric models used to simulate streamflow forecasts. Section 3 details the nonparametric FMFE model and examines the properties of simulated forecast uncertainty. Section 4 demonstrates an application of the model to simulation of streamflow forecast. Section 5 presents a decision making analysis and illustrates effect of forecast skill on forecast-based reservoir operation. Section 6 provides the discussions and conclusions.

2. Simulation of streamflow forecast

Using time indices s and t, and denoting $f_{s,t}$ as the forecast of streamflow q_t that is made at period s, and the forecast horizon as H, the forecasts made at period s form a forecast vector:

$$F_{s,-} = [f_{s,s} \quad f_{s,s+1} \quad f_{s,s+2} \quad \dots \quad f_{s,s+H}] \tag{1}$$

$H+1$ forecasts are made at period s. Moreover, $H+1$ forecasts correspond to q_t made during the preceding periods $t-H, t-H+1, \dots,$ and $t-1$, as well as period t, form the following vector:

$$F_{-,t} = [f_{t-H,t} \quad f_{t-H+1,t} \quad f_{t-H+2,t} \quad \dots \quad f_{t,t}] \tag{2}$$

$F_{s,-}$ and $F_{-,t}$ are differentiated in Eqs. (1) and (2), respectively. We present a brief summary of the stochastic models used in the simulation of streamflow forecasts.

2.1. Simulation of forecasts made in one period

Forecast uncertainty can generally be indicated by the gap between forecast $f_{s,t}$ and the real value of streamflow q_t [20,28,35]. In the deterministic case, forecast uncertainty is represented by forecast error $e_{s,t}$,

$$e_{s,t} = f_{s,t} - q_t \tag{3}$$

Following Eqs. (1) and (3), the uncertainty of the streamflow forecasts generated during period s is characterized by the following vector:

$$E_{s,-} = [e_{s,s} \quad e_{s,s+1} \quad e_{s,s+2} \quad \dots \quad e_{s,s+H}] \tag{4}$$

For the fixed period s, the forecast uncertainty in $f_{s,t}$ tends to increase with t, i.e., a longer lead time leads to increased uncertainty [22,23], as shown in Fig. 1.

For the sake of simplicity, the stochastic models of forecast uncertainty can assume that $e_{s,s+i}$ ($i = 0,1,2,\dots,H$) are mutually independent, which allows for the independent simulation of $e_{s,s+i}$. The assumption of Gaussian distribution leads to the following [23]:

$$e_{s,s+i} \sim N(m_i, \sigma_i^2) \quad (i = 0,1,2,\dots,H) \tag{5}$$

In Eq. (5), m_i and σ_i^2 are the mean and variance of $e_{s,s+i}$, respectively. Thus, $e_{s,s+i}$ is simulated by:

$$e_{s,s+i} = m_i + \sigma_i \varepsilon_i \tag{6}$$

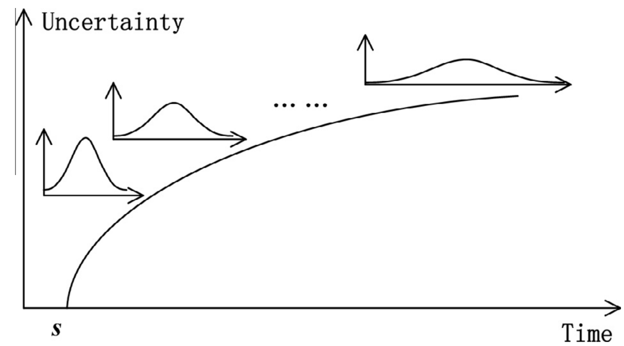

Fig. 1. Longer forecast lead time leads to greater forecast uncertainty.

In Eq. (6), ε_i is a standard Gaussian random number, i.e., $\varepsilon_i \sim N(0, 1^2)$. Other statistical distributions, e.g., log-Gaussian distribution and Gamma distribution, have also been used to simulate forecast uncertainty [12,28].

The variance σ_i^2 of $e_{s,s+i}$ (Eq. (5)) has often been used as an indicator of the magnitude of forecast uncertainty [19,35,36]. In simulations of single-period forecast uncertainties, the variance is usually set as:

$$\sigma_0^2 \leqslant \sigma_1^2 \leqslant \sigma_2^2 \leqslant \dots \leqslant \sigma_H^2 \tag{7}$$

This equation indicates the characteristic longer lead time induces greater forecast uncertainty. The variance is also set as:

$$\sigma_H^2 \leqslant \mathrm{var}(q_{s+H}) \tag{8}$$

where $\mathrm{var}(q_{s+H})$ indicates streamflow variability within time period $s+H$. This equation implies that the magnitude of forecast uncertainty cannot be greater than that of streamflow variability. Otherwise, having no forecast would be a better option [23].

Comparison between forecast uncertainty and streamflow variability indicates the forecast skill. Denoting the variability of q_{s+i} ($i = 0,1,2,\dots,H$) as $\mathrm{var}(q_{s+i})$ and the uncertainty of the corresponding forecast $f_{s,s+i}$ as σ_i^2 ($i = 0,1,2,\dots,H$), the coefficient of prediction (C_p) measures the fraction of streamflow variability explained by the forecast [22,23,29], i.e.,

$$\sigma_i^2 = (1 - C_p)\mathrm{var}(q_{s+i}) \quad (i = 0,1,\dots,H) \tag{9}$$

In Eq. (9), the case $C_p = 1$ represents perfect forecast skill, such that σ_i^2 becomes zero; the case $C_p = 0$ stands for no forecast skill, such that $\sigma_i^2 = \mathrm{var}(q_{s+i})$. The phenomenon whereby C_p decreases with lead time implies that σ_i^2 increases with i, which indicates decreasing forecast skill and increasing uncertainty with increasing forecast lead time [23].

Eqs. (4)–(9) illustrate the simulation steps for independent forecast uncertainties. Incorporating the variance–covariance matrix $VCVE$ enables the simulation of correlated uncertainties [38], i.e.,

$$VCVE = \begin{pmatrix} \mathrm{ve}_0 & \mathrm{cove}_{0,1} & \mathrm{cove}_{0,2} & \cdots & \mathrm{cove}_{0,H} \\ \mathrm{cove}_{1,0} & \mathrm{ve}_1 & \mathrm{cove}_{1,2} & \cdots & \mathrm{cove}_{1,H} \\ \mathrm{cove}_{2,0} & \mathrm{cove}_{2,1} & \mathrm{ve}_2 & \cdots & \mathrm{cove}_{2,H} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathrm{cove}_{H,0} & \mathrm{cove}_{H,1} & \mathrm{cove}_{H,2} & \cdots & \mathrm{ve}_H \end{pmatrix} \tag{10}$$

In Eq. (10), $\mathrm{cove}_{i,j}$ ($i, j = 0,1,2,\dots,H$) denotes the covariance of $e_{s,s+i}$ and $e_{s,s+j}$; ve_i is the variance of $e_{s,s+i}$, which is also denoted as σ_i^2 in Eq. (5). Variance–covariance matrices are semi-definite. Through Cholesky decomposition, $VCVE$ can be decomposed into the product of a matrix multiplied by its transpose, i.e.,

$$VCVE = VE^{*} VE^{T} \tag{11}$$

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