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A Bayesian model averaging method for the derivation of reservoir operating rules

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SUMMARY

Because the intrinsic dynamics among optimal decision making, inflow processes and reservoir characteristics are complex, functional forms of reservoir operating rules are always determined subjectively. As a result, the uncertainty of selecting form and/or model involved in reservoir operating rules must be analyzed and evaluated. In this study, we analyze the uncertainty of reservoir operating rules using the Bayesian model averaging (BMA) model. Three popular operating rules, namely piecewise linear regression, surface fitting and a least-squares support vector machine, are established based on the optimal deterministic reservoir operation. These individual models provide three-member decisions for the BMA combination, enabling the 90% release interval to be estimated by the Markov Chain Monte Carlo simulation. A case study of China's the Baise reservoir shows that: (1) the optimal deterministic reservoir operation, superior to any reservoir operating rules, is used as the samples to derive the rules; (2) the least-squares support vector machine model is more effective than both piecewise linear regression and surface fitting; (3) BMA outperforms any individual model of operating rules based on the optimal trajectories. It is revealed that the proposed model can reduce the uncertainty of operating rules, which is of great potential benefit in evaluating the confidence interval of decisions.

1. Introduction

The optimal operation of a reservoir is a difficult issue in water resources management (Guo et al., 2012; Li et al., 2010). For deterministic reservoir operation with a pre-determined inflow, it is possible to determine the optimal solution (Labadie, 1994; Yeh, 1985). Techniques such as dynamic programming (Bellman, 1956) and improved dynamic programming (e.g., progressive optimality algorithm (Turgeon, 1981), discrete differential dynamic programming (Heidari et al., 1971)), genetic algorithms (Chang et al., 2005; Oliveira and Loucks, 1997) and particle swarm optimization (Guo et al., 2013; Trelea, 2003) have been used to find optimal solutions for deterministic reservoir operation.

However, deterministic optimization with perfect inflows knowledge is difficult to apply into the real operations. Therefore, it is necessary to derive reservoir operating rules because of limitations on inflow forecasting techniques (Wei and Hsu, 2008). The reservoir operating rules determine the rate at which water is released based on currently available information, such as the current storage and forecast inflow. Either implicit stochastic optimization (ISO) (Celeste and Billib, 2009; Young, 1967) or explicit stochastic optimization (ESO) (Stedinger et al., 1984) can be used to derive the reservoir operating rules.

Using ISO, various functional forms have been applied to the derivation of operating rules. These include linear regression (LR) (Liu et al., 2011b, 2014; Young, 1967), fuzzy models (Russell and Campbell, 1996), genetic programming (Li et al., 2014), two-dimensional surface models (SURF) (Celeste and Billib, 2009; Celeste et al., 2005), Bayesian networks (Malekmohammadi et al., 2009) and support vector machines (SVMs) (Ji et al., 2014; Karamouz et al., 2009; Suykens et al., 2002; Suykens and Vandewalle, 1999). Piecewise linear regression (PL-REG), SURF

Abbreviations: BMA, Bayesian model averaging; COR, conventional operating rules; ESO/ISO, explicit/implicit stochastic optimization; LR, linear regression; LS-SVM, least-squares support vector machine; MCMC, Markov Chain Monte Carlo; NRMSD, normalized root mean square deviation; PL-REG, piecewise linear regression; RMSE, root mean square error; SURF, surface fitting; TDDP, two-dimensional dynamic programming.

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and least-squares SVM (LS-SVM) have been widely used. By analyzing the optimal trajectory, Liu et al. (2014) concluded that LR operating rules were suitable for the hydropower operation of China's Three Gorges Reservoir, and implemented an uncertainty analysis for future parameter values. Celeste and Billib (2009) determined that the SURF model was the best in terms of overall performance for the Epitácio Pessoa Reservoir, whereas Ji et al. (2014) proposed SVM operating rules for the Jinsha Reservoirs system, demonstrating the effectiveness of SVMs for such scenarios. Although the above LR, SURF and SVM operating rules have been successfully used, they are black models and should have model uncertainty. Therefore, it is necessary to analyze and evaluate the model uncertainty involved in reservoir operating rules. Bayesian model averaging (BMA) (Hoeting et al., 1999) can be used to analyze the uncertainty of selecting models by combining a number of individual models with different weights. BMA has been widely applied in the field of water resources, such as for hydrological forecasting (Ajami et al., 2007; Raftery et al., 2005) and groundwater modeling (Rojas et al., 2008). Raftery et al. (2005) used BMA to calibrate 48-h forecasts of surface temperature in the Pacific Northwest, and showed that BMA outperformed all individual models. Consequently, we expect that BMA can be used to combine various reservoir operating rules to generate a new decision and tackle model uncertainty.

The Expectation–Maximization (EM) (Vrugt et al., 2008) and Markov Chain Monte Carlo (MCMC) (Vrugt et al., 2008, 2009) algorithms can be used to estimate the BMA parameters $\theta = \{w_1, w_2, \ldots, w_K, \sigma^2\}$. The EM algorithm is easy to implement, but imposes a heavy computational burden because of its high dimensionality (Vrugt et al., 2008). MCMC simulation estimates the most likely values of the BMA weights and variances, as well as the underlying posterior probability density function. MCMC can be used to explore the parameter space using multiple different trajectories (also called Markov Chains). Various methods are used to generate Markov Chains, including the Metropolis algorithm, Metropolis–Hastings algorithm and Gibbs' algorithm. The DiffeRential Evolution Adaptive Metropolis (DREAM) algorithm is an increasingly widespread method, applied the Shuffle Complex Evolution Metropolis (SCEM-UA) algorithm for global optimization (Laloy and Vrugt, 2012; Sadegh and Vrugt, 2014; Vrugt et al., 2008), allowing N different Markov Chains to run simultaneously in parallel.

The purpose of this study is to use BMA to derive integrated and robust reservoir operating rules with less uncertainty and more reliable to the optimal decision (say robust performance) by combining three individual models. Based on the optimal trajectory of deterministic reservoir operation, piecewise linear regression (PL-REG), SURF and least-squares SVM (LS-SVM) are used to derive individual operating rules. BMA model combines these models to generate a new decision with robust performance by using a confidence interval.

The remainder of this paper is organized as follows. In Section 2, we describe the optimal deterministic reservoir operation model and individual reservoir operating rules of PL-REG, SURF and LS-SVM, and then use BMA to construct integrated reservoir operating rules. Section 3 describes a case study of China's the Baise reservoir, including the results of COR, TDDP, individual reservoir operating rules (PL-REG, SURF and LS-SVM) and BMA. The performance of BMA is compared with that of the conventional, optimal and individual operating rules in Section 4. Finally, our conclusions are given in Section 5.

2. Methodology

As shown in Fig. 1, the BMA operating rules are derived as follows:

(1) The optimal deterministic reservoir operation model is established, and its optimal solution is obtained using simplified two-dimensional dynamic programming (TDDP) (Section 2.1).
(2) Based on the above optimal trajectory, the individual PL-REG, SURF and LS-SVM models are used to derive the reservoir operating rules (Section 2.2). The optimal trajectory, which is the optimal solution to the deterministic reservoir optimization model, is used as the samples to derive the reservoir operating rules by using the fitting method in the ISO framework.
(3) The BMA reservoir operating rules are derived by combining the three individual operating rules (Section 2.3).

2.1. Optimal deterministic reservoir operation

The difficulty of balancing upstream and downstream benefits has made flood control a longstanding challenge. Under the condition that the reservoir downstream is safe, we considered minimizing the maximum water level as the only objective:

$$\min Z_m^* \Longleftrightarrow \min \left\{ \sum_{t=1}^{T} \{V(t)\}^2 \right\} \tag{1}$$

where Z_m^* is the maximum water level; $V(t)$ is the reservoir storage at time t; T is the number of time periods; and the square of $V(t)$ makes it easy to search the objective. Minimizing the maximum water level Z_m^* is equivalent to minimizing the sum of the square of $V(t)$.

The water balance equation, water storage capacity, safe streamflow at the flood control station, release capacity, incremental release amount between consecutive time periods and channel routing constraints (Hsu and Wei, 2007; Zhou and Guo, 2013) are as follows:

$$\frac{I(t) + I(t+1)}{2}\Delta t - \frac{R(t) + R(t+1)}{2}\Delta t = V(t+1) - V(t) \tag{2}$$

$$V_{\min} \leqslant V(t) \leqslant V_{\max} \tag{3}$$

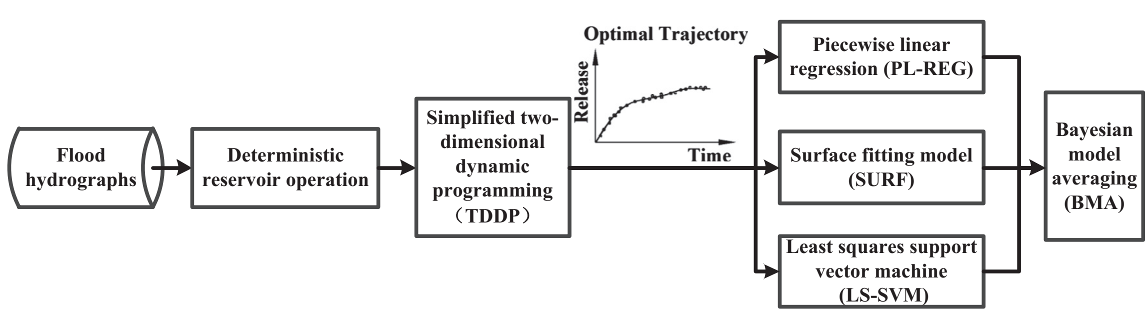

Fig. 1. Flowchart for the derivation of BMA operating rules.