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Parameter uncertainty analysis of reservoir operating rules based on implicit stochastic optimization

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SUMMARY

Reservoir operating rules are often derived using either a fitting or a simulation-based optimization method in the context of implicit stochastic optimization. Analysis of the parameter uncertainty in reservoir operating rules and their impact is necessary for robust solutions. In the present study, parameter uncertainty for reservoir operating rules is analyzed using two statistical methods, linear regression (LR) and Bayesian simulation (BS). LR estimates the confidence interval based on fitting the operating rules to the optimal deterministic solution. BS deals with the operating rule parameters as stochastic variables and treats the goodness-of-fit to the optimal deterministic solution or the operation profits as the likelihood measure. Two alternative techniques, the generalized likelihood uncertainty estimation (GLUE) and Markov Chain Monte Carlo method (MCMC), are implemented for the BS uncertainty analysis. These methods were applied to the operating rules of China's Three Gorges Reservoir. The LR performed less than the BS, and the MCMC outperformed the GLUE. Even for the BS methods, the operation profits criterion was better than the goodness-of-fit criterion for deriving the reservoir operating rules.

1. Introduction

Reservoirs are typically operated using operating rules, which specify operational decisions (e.g., releases) as a function of available information (Li et al., 2010b; Oliveira and Loucks, 1997), such as the current reservoir water level and the hydro-meteorological conditions (Guo et al., 2004). Implicit stochastic optimization (ISO) (Young, 1967) is an efficient alternative to explicit stochastic optimization (Stedinger et al., 1984; Tilmant et al., 2008) for considering hydrologic stochasticity, and has often been used in studies to derive optimal reservoir operating rules (e.g., Bhaskar and Whitlatch Jr., 1980; Celeste and Billib, 2009; Labadie, 2004; Lund and Ferreira, 1996; Koutsoyiannis and Economou, 2003; Rani and Moreira, 2010). ISO enables most characteristics of stochastic inflows, including spatial and temporal correlations among unregulated runoff, to be implicitly incorporated into reservoir operations modeling by inputting observed or synthetic samples (Labadie, 2004). As a result, ISO has become one of the most reliable methods of reservoir modeling (Celeste and Billib, 2009; Rani and Moreira, 2010; Simonovic, 1987; Wurbs, 1993).

Two approaches can be used to derive optimal operating rules within an ISO framework when the functional form of the operating rules has been pre-determined: fitting methods and simulation-based optimization (SBO) methods. With fitting methods, the reservoir operating rules are derived from deterministic optimization models using either linear regression (LR) (Bhaskar and Whitlatch Jr., 1980; Young, 1967) or nonlinear fitting methods, such as nonlinear regression (Young, 1967), artificial neural networks (Liu et al., 2006), fuzzy inference (Chang and Chang, 2001; Han et al., 2012) and decision trees (Wei and Hsu, 2008). However, the maximum goodness-of-fit criterion for establishing the operating rules may not always be appropriate to produce the best rules (Bhaskar and Whitlatch Jr., 1980).

Partly because of the deficiencies in fitting methods, SBO (Koutsoyiannis and Economou, 2003; Nalbantis and Koutsoyiannis, 1997) has become more widely used (Celeste and Billib, 2009; Rani and Moreira, 2010). SBO methods directly optimize performance measures, such as maximizing profits (e.g., hydropower generation) or minimizing loss (e.g., flood risk), by adjusting operating rule parameters as decision variables in an iterative simulation-based search algorithm (Chen et al., 2007;

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Koutsoyiannis and Economou, 2003; Ngo et al., 2007). Determination of the operating rule parameters is similar to that of parameter calibration in a hydrologic model (Table 1), in which the objective functions are the maximization of net benefits in reservoir operations and matching the observed data in a hydrologic model, respectively. Indeed, both problems are inverse problems, which are a general framework to convert observed measurements into information describing a system.

ISO involves uncertainty in the parameters characterizing the optimality of derived operating rules because of the uncertainty inherent in reservoir operations models. There is intrinsic uncertainty in the dynamics of inflow processes and uncertainty in knowledge of physical parameters such as hydro-meteorological parameters and reservoir characteristics (e.g., reservoir elevation-storage relationship, and uncertainty in the economic processes and parameters that describe operational performance). Specifically, it is difficult to identify the actual optimal operating rules using ISO because the rules depend on the historical or simulated inflow. As a result, "errors" always exist between the true optimal and estimated decision. When these methods are used, it is desirable to determine a method for analysis and evaluation of the resulting uncertainty in the derived reservoir operating rule parameters. This study deals with analysis of uncertainty associated with reservoir operating rule parameters, which has seldom been addressed in the literature.

Analysis of operating rule parameter uncertainty is required for generating robust reservoir operation rules, especially from the following two aspects (Liu et al., 2011b). (1) Alternative rules: optimization should not be used to find the best solution, but rather to identify a relatively small number of good alternatives that can later be tested, evaluated and improved (Loucks and van Beek, 2005). In contrast to identifying an optimal parameter for reservoir operating rules, uncertainty analysis assumes these parameters are random variables and therefore provides a set of decisions and their confidence intervals. These confidence intervals provide more information, including the robust decision (say median) and the probability coverage for the best decision, than a single decision. (2) Sensitivity analysis: uncertainty analysis can be used to determine how sensitive an objective is to variations in the reservoir decisions, and hence the critical and important periods for reservoir operation can be identified by analyzing the confidence interval.

Uncertainty analysis has received increasing attention in water resources research over the last two decades (Montanari, 2007; Pappenberger and Beven, 2006). Most of these studies have focused on hydrologic models (e.g., Beven and Freer, 2001; McMillan and Clark, 2009; Tolson and Shoemaker, 2008; Vrugt et al., 2003; Yang et al., 2008; Zhang et al., 2013), including groundwater models (Mugunthan and Shoemaker, 2006) and, frequency analysis (El Adlouni and Ouarda, 2009; Reis Jr. and Stedinger, 2005) and water quality (Deviney Jr. et al., 2012; Xu and Qin, 2013). In general, uncertainty analysis in model prediction (simulation) involves the quantification of uncertainty in the model inputs, parameters, structure, and observations (Liu and Gupta, 2007). In this study, we only discuss parameter uncertainty.

Because of the parallels between parameter estimation for both hydrologic models and operating rule parameter derivation models (Table 1), uncertainty analysis approaches applied into the former also can be used to the latter. Two widely used mutually independent uncertainty analysis approaches (Montanari et al., 2009), non-probabilistic generalized likelihood uncertainty estimation (GLUE) (Beven and Binley, 1992) and probabilistic Bayesian methods, were implemented for uncertainty analysis in this study. The popular Markov Chain Monte Carlo (MCMC) (Chib and Greenberg, 1995) algorithm has been used for the probabilistic Bayesian inference. GLUE was proposed for the investigation of the hydrologic modeling uncertainty by producing the prediction limits for the modeled streamflow series and a set of behavioral parameter sets (Beven and Binley, 1992), while MCMC was primarily used to simulate observations from unwieldy distributions by constructing a Markov Chain as samplers (Chib and Greenberg, 1995).

The purpose of this paper is to demonstrate how parameter uncertainty analysis can be applied to reservoir operating rules and highlight the importance of such analysis for generating more robust reservoir operation rules. The remainder of this paper is organized as follows. In Section 2, we describe optimal operating rules and present two alternative methods of estimating rule parameter uncertainty, LR and Bayesian simulation (BS). The BS method is implemented with GLUE and the MCMC algorithm. Section 3 describes a case study application to China's Three Gorges Reservoir (TGR). Section 4 provides further discussion of the analysis methods and the implication of the analysis results for more effective solutions to reservoir operations. Finally, conclusions are given in Section 4.

2. Methodology

Two approaches for analyzing the uncertainty associated with derived reservoir operating rules are presented and assessed: LR and BS. Assessing these methods depends on knowledge of the theoretical optimal releases. Therefore, a reservoir operation optimization model is first introduced. This is followed by a description of operating rules, which are often used in practice. The uncertainty analysis methods are then described.

2.1. Deterministic reservoir operations

The optimal deterministic reservoir operation solution was needed to evaluate the reservoir operating rules, since optimal operations reveal the maximum potential benefit that can be achieved under perfect hydrologic foresight.

For simplicity, we considered the following yearly reservoir operation model (Liu et al., 2011b), which maximizes average annual hydropower generation E as the only objective:

$$\max E = \frac{1}{m}\sum_{i=1}^{n}\sum_{j=1}^{m} N_{i,j}\Delta t_{i,j} \tag{1}$$

where n is the number of time steps per year and m is the number of years, $\Delta t_{i,j}$ is the time step length and $N_{i,j}$ is power output (kW) during time period i in the jth year, respectively. $N_{i,j}$ is a function of release $R_{i,j}$ (m^3/s) and water head $H_{i,j}$ (m). Specifically, power output is calculated as $N_{i,j} = \min(KR_{i,j}H_{i,j}, N_{\max})$, where K is a constant coefficient (m/s^2, unit same with gravitational acceleration) that

Table 1
Analogy of the parameter calibration of the hydrologic model and derivation of the operating rules of the reservoir operation model.

	Hydrologic model parameter calibration	Operating rule parameter derivation
Objective function	Fitting to the observed flow	Maximization of profits
Parameter	Hydrologic parameters	Operating rules parameters
Simulation model	Hydrologic simulation	Reservoir operation simulation