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Research papers

Study on optimization of the short-term operation of cascade hydropower stations by considering output error

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ABSTRACT

The study of reservoir deterministic optimal operation can improve the utilization rate of water resource and help the hydropower stations develop more reasonable power generation schedules. However, imprecise forecasting inflow may lead to output error and hinder implementation of power generation schedules. In this paper, output error generated by the uncertainty of the forecasting inflow was regarded as a variable to develop a short-term reservoir optimal operation model for reducing operation risk. To accomplish this, the concept of Value at Risk (VaR) was first applied to present the maximum possible loss of power generation schedules, and then an extreme value theory-genetic algorithm (EVT-GA) was proposed to solve the model. The cascade reservoirs of Yalong River Basin in China were selected as a case study to verify the model, according to the results, different assurance rates of schedules can be derived by the model which can present more flexible options for decision makers, and the highest assurance rate can reach 99%, which is much higher than that without considering output error, 48%. In addition, the model can greatly improve the power generation compared with the original reservoir operation scheme under the same confidence level and risk attitude. Therefore, the model proposed in this paper can significantly improve the effectiveness of power generation schedules and provide a more scientific reference for decision makers.

1. Introduction

Hydropower is a renewable and clean energy resource (Ibrahim, 2010; Wu and Chen, 2012). The use of more hydropower energy instead of coal resources has important significance in today's era of resource scarcity, and the construction of reservoirs can meet this demand. Additionally, a reservoir has several functions, such as power generation, irrigation, and flood control (Urbaniak et al., 2012), to give reservoirs a more important role and produce more benefits, research regarding the optimal operation of hydropower stations has become of increasing interest (Chang et al., 2010; Li et al., 2014; Ji et al., 2015; Zhang et al., 2013, 2015, 2016).

As we know, in actual operation and management of hydropower stations, power generation schedules are often developed based on forecasting inflow rather than actual inflow. Thus, imprecise forecasting and large forecasting error may appear owing to the randomness and regional characteristics of runoff. For this reason, the original power generation schedule may not be implemented smoothly and need to be adjusted during operation process; this behavior may not only affect the benefit of hydropower stations but also reduce the utilization rate of water resource. Therefore, attention should be paid on uncertainties when developing power generation schedules.

Although there are several uncertainties that need to be considered, forecasting inflow error is regarded as the primary risk for reservoir operation. In general, there are two approaches to reducing the influence of forecasting error. The first approach mainly focuses on the improvement of forecasting accuracy, from this perspective, forecasting models are modified and developed to enhance its accuracy and further reduce the forecasting error and operation risk as proposed by many previous studies, e.g., Lima et al. (2014) developed a Bayesian dynamic linear model that incorporated seasonal and autoregressive components to present better performance on predictions. Bai et al. (2015) used ensemble empirical mode decomposition and Fourier spectrum to extract multiscale features and proposed a multiscale deep feature

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learning method to improve inflow forecasting accuracy effectively. Cui et al. (2016) improved the Thomas–Fiering and wavelet neural network models through optimizing the model parameters to enhance the accuracy of forecasting reservoir inflow, etc. The researches above provide significant contributions to improving the prediction accuracy and address the uncertainty to some extent.

The second approach is about assessment on the influence of errors, in this point, forecasting error always exists in the whole operation process, hence it should be quantified to conduct the distribution analysis then further realize the optimal operation of reservoir under an acceptable level as discussed in many researches, e.g., Jiang et al. (2015) regarded the forecasting error as a fuzzy variable and applied it to optimize the operation water level based on credibility theory. Xie et al. (2015) studied a forecasting dispatching chart method by considering the forecasting error, etc. Previous researches provided many valuable references with considering impacts of forecasting error so that the optimal operation of reservoir can be better realized. It is well known that forecasting error directly causes output error of hydropower stations which is the major risk of power generation scheduling, attentions should be given on output error when developing power generation schedule. However, so far as we know, few researches concerning output error generated by forecasting error were studied to realize the reservoir optimal operation.

Value at Risk (VaR) has a good ability to express the maximum risk of the events and it has been successfully applied in many fields. Jang and Park (2016) used VaR to present a model of optimal portfolio choice for a fund manager who allocates her wealth between risky and riskless assets. Potjagailo (2017) developed a factor-augmented VAR approach to analyze the spillover effects from a Euro area monetary policy. In addition, VaR is also widely applied to stock market and insurance contract (Caporale et al. ,2016; Gao and Zhou, 2016; Lu et al., 2016). However, to the best of the author's knowledge, nowadays, VaR has not been applied into the reservoir operation to address the influence of the output error.

Thus, the concept of Value at Risk (VaR) is introduced to represent the maximum possible output loss of power generation schedules owing to forecasting error to develop a short-term reservoir optimal operation model considering output error. For the solving of the model, the general optimization algorithms such as genetic algorithm (GA), dynamic planning (DP), progressive optimality algorithm (POA) and so on cannot meet the solving requirement because the result derived by the model should not only be the optimal solution but also have a high assurance. so an extreme value theory-genetic algorithm (EVT-GA) is proposed in the paper, extreme value theory (EVT) is first applied to quantify the output loss while genetic algorithm (GA) is to realize the diversity of operation schemes and select the schemes with its genetic operation. In the end, optimal operation scheme can be derived with consideration of balancing risk and benefits which can effectively reduce the influence of output error incurred by forecasting error during operation process.

The remainder of the paper is organized as follows: Section 2 will describe the modeling approaches. In Section 3, the model will be applied to the cascade reservoirs of the Yalong River Basin in south China. Section 4 will illustrate detailed results and discussion, and the feasibility and rationality of the model will be further verified. Finally, Section 5 will provide the conclusions.

2. Methodology

Generally, when the decision makers develop a power generation schedule, they often use the traditional objective function to calculate as follows.

$$E = \max \sum_{i=1}^{T} K_i q_t^i H_t^i \Delta t \tag{1}$$

where E is the total power generation of the hydropower stations in the whole operation period, unit: kWh; K_i is the output coefficient of the ith reservoir; q_t^i is the average outflow through the turbines of the ith reservoir in the tth period, unit: m^3/s; H_t^i is the net water head of the ith reservoir in the tth period, unit: m; Δt is the duration of an operation period, unit: minute; T is the total number of periods.

When solving formula (1), the input inflow data is derived by forecasting. However, the original power generation schedule may not be implemented smoothly due to the influence of the inevitable forecasting error. Thus, formula (1) is not proper because it does not consider the influence of the forecasting error. In order to address the problem, the concept of Value at Risk (VaR) is introduced to develop a short-term reservoir operation model considering output error, and an extreme value theory-genetic algorithm (EVT-GA) is proposed to solve the model. These approaches are introduced in following subsections, respectively.

2.1. Optimal short-term reservoir operation model obtained by considering output error

2.1.1. Objective function

The concept of the Value at Risk (VaR) was proposed by an international private research institutions in 1993 and explicitly introduced by the Basel Committee on Banking Supervision in 1996 (Wang and Huang, 2016), which expresses the maximum possible loss of the investment portfolio over a certain time horizon τ at a given confidence level α. Now, it has become a popular method to assess the risk of events because of its primarily smaller data requirements, ease of back testing and calculation. In normal market conditions, its expression can be represented as:

$$\begin{cases} VaR = \omega_0 \times VaR_p \\ \Pr(\Delta r(\tau) < VaR_p) = 1 - \alpha \end{cases} \tag{2}$$

where ω_0 represents the total cost; VaR_p is the worst yield rate at the given confidence level; Pr $(\Delta \mathrm{r}\ (\tau) < VaR_p)$ represents the occurrence probability of the events "$r\ (\tau) < VaR_p$"; α is the confidence level.

When implementing the planned power generation schedule, the actual power generation may not be able to meet the requirement as planned due to the existence of output error, we regard the discrepancy between actual power generation and planned power generation as output loss of the planned power generation. What we need to do is to obtain the maximum possible loss so that to know the influence of forecasting error in each schedule; Based on the definition of the VaR, we use it to represent the maximum possible output loss of power generation schedules owing to forecasting error. In addition, the main objective of cascade reservoirs operation is to make full use of water resources, and power generation is one of the major functions for cascade reservoirs. The power generation of cascade hydropower stations depends on many factors, e.g., inflow, the length of the operation period, the operation schemes, etc. On the basis of considering all kinds of factors above, the objective function of the model can be described as follows.

$$E = \max \left\{ (1 - \gamma VaR_p) \sum_{i=1}^{T} K_i q_t^i H_t^i \Delta t \right\} \tag{3}$$

where E is the total power generation of the hydropower stations in the whole operation period, unit: kWh; γ represents the risk attitude of the decision maker, $\gamma \in [0,1]$, when the value of γ is closer to 1, it indicates the attitude of decision maker is more towards