Risk Analysis of Dynamic Water Level Setting of Reservoir in Flood Season Based on Multi-index

Zhenyu Mu[1] · Xueshan Ai[1,2] · Jie Ding[1] · Kui Huang[3] · Senlin Chen[1] · Jiajun Guo[1] · Zuo Dong[1]

Abstract

Long-term operation of the reservoir at the flood limit water level (FLWL) in the flood season is not conducive to the exertion of the comprehensive benefits of the reservoir, especially in the flood free period, causing a certain waste of resources. In order to make full use of water resources and avoid the risk of flooding due to extreme events, this paper proposes a dynamic water level decision-making model in flood free period, which considers the utmost of resources, effective response measures for possible catastrophic floods and the credible decision method, thus improving the operational benefit of hydropower station in the flood season and reducing flood control risk. The proposed model includes four modules. Firstly, historical data and the fuzzy statistical test method are used to divide the flood season into multiple stages. Secondly, the maximum inflow process in the effective forecast period of flood forecast in each stage is selected, and according to this inflow process, the operating limited water level (OLWL) in the flood free period of each stage is determined based on the reservoir discharge capacity, then the operating water level range and discharge ratio are discretized. Thirdly, multi-order Monte Carlo Markov Chain (MCMC) and Monte Carlo method are used to calculate the risk rate, and the scheme set is established by the three variables of power generation benefit, discharge ratio and risk rate. Finally, the weighted Topsis method, considering subjective and objective weighting method, is applied to determine the best scheme. This method has been verified in Youjiang reservoir in Yujiang River Basin. The main conclusions are as follows: (1) Combined with the discharge in the forecast period, the reservoir operating water level has a certain raising space in the flood free period. (2) The multi-order MCMC method effectively reflects the relationship between adjacent periods of runoff forecast error, and its simulation process is closer to the reality. (3) The Topsis method, which combines AHP with entropy weight method, can fully consider the characteristics of power generation efficiency, flow ratio and risk rate, and can effectively select satisfactory schemes from non-inferior schemes. This

Highlights

- Operating limited water level (OLWL) has been defined for dynamic water level setting.
- Study on the risk analysis of reservoir flood controls operation during pre-discharge period.
- The optimal scheme considers possible extreme flood events and provides reserved space for it.
- More reliable weights have be obtained by combining subjective and objective methods.

Extended author information available on the last page of the article

method provides a new idea for determining the operating water level of the reservoir in the flood season.

1 Introduction

Hydropower is the most reliable, mature, stable and currently accounting for the largest proportion of clean energy, whose development can help relieve the environmental problems caused by the shortage of traditional fossil energy and fuel consumption, and promote carbon neutrality (Liu et al. 2022; Moser et al. 2021). Furthermore, due to the problem of low operation and management level in reservoir regulation, the efficient utilization of hydropower station and the development of key technologies still need further research, and the selection of the operation decision with corresponding risk research in the flood season is a significant research direction. On the one hand, with the continuous improvement of the forecast accuracy, the effective forecast period of flood forecast will continue to extend, when there is excess water in the flood free period, water can be stored in the reservoir rather than abandoned to increase the benefit of power generation, and the water level can be dropped back to the flood limit water level (FLWL) in time before flood comes through pre-discharge, in order to ensure the safety of flood control; On the other hand, affected by the forecast uncertainty and other factors, the higher the operating water level in the flood free period, the greater the risk of the water level returning to the FLWL. Moreover, climate change is causing more extreme flood events (Reichstein et al. 2021; Miyake et al. 2021), and the scheduling schemes, which were made only based on power generation benefits and the risk rate calculated based on historical data, are not suitable to deal with large-scale flood events that may occur in the future. Therefore, formulating a dynamic water level setting method of reservoir in the flood season is of great research significance for improving reservoir operational efficiency, avoiding the high risk, and taking the possible extreme floods into account.

Forecast uncertainty is the primary source of risk regarding reservoir flood control operation, affecting both reliability and safety of the entire system, due to the influence of factors such as model parameter errors, the prediction errors in each period of runoff forecast has a certain correlation (Zhao 2013; Huang et al. 2022). In order to describe this correlation, Copula function (Xu et al. 2021; Li et al. 2022; Dodangeh et al. 2020), Bayesian network (Lu et al. 2020), Monte Carlo Markov Chain (Hadfield 2010; Lian et al. 2021) have been applied to runoff simulation in recent years, theoretically, when the forecast period is long enough, inputting the hourly updated hydrological forecast into the operation model can update the operation decision hourly, thus making full use of the hydrological forecast information and improving the benefits of the reservoir system (Zhao et al. 2011). Moreover, combined with the simulation of uncertain factors such as runoff forecast error, the possible risks of operational decision can be better analyzed, thus providing clear guidance for reservoir operation.

There is an interactive and competitive relationship between risk and power generation benefit, and its competition intensity will change with the change of stages (Yao et al. 2019). In order to describe the competition relationship between risk and benefit, it is necessary to divide the flood season into multiple stages, and adopt multiple FLWLs

instead of a single and constant value in the whole flood season (Fang et al. 2007; Zhou et al. 2018). After analyzing and improving the existing research results, segmentation methods can be mainly divided into six categories: fractal, cluster analysis, change point analysis, fuzzy set analysis, projection pursuit and Fisher the optimal break up. For example, Pan et al. (2018) proposed a quantitative measurement method–Seasonal exceedance probability (SEP) to evaluate the flood season staging scheme. Zhou (2022) carried out theoretical analysis on flood season segmentation methods and put forward a framework for proper flood season segmentation through comparison between different segmentation methods.

In order to make a decision by integrating risk and power generation benefit, many decision-making methods have been applied. For example, Chen et al. (2021) combined entropy weight method with Topsis method to evaluate flood risk and loss in southern China, making up for the lack of research on the comparison of flood risk and benefit loss; Li et al. (2021) determined the benefit and risk index set of phased control of FLWL, and established a risk–benefit multi-objective collaborative decision-making model to solve the optimal decision-making, so as to effectively combine the benefit and risk; Xu et al. (2020) established a two-stage stochastic optimization model to find a balance between water shortage and flood risk. The above methods effectively consider the risk and benefit factors. Nevertheless, due to the particularity of risk indicators, it is difficult to measure their weight by objective methods, so it is necessary to consider subjective factors in decision-making to find a better scheduling scheme.

The previous research shows that short-term runoff forecast has been utilized in water resources management and other fields, and the methods of flood season segmentation are also very fruitful, which provide a basis for the effective combination of risk and benefit in the process of reservoir operation. Nevertheless, the existing results are still difficult to solve three major problems: First, although previous literature reports success in the field of coordinating benefits and risks by changing the FLWL, few studies pay attention to the waste of resources when the reservoir is maintained at the FLWL in the flood free period. Second, affected by climate change, the frequency of extreme weather is increasing, and the existing research lacks effective response measures for possible catastrophic floods in the future. Third, the particularity of risk rate and other indicators is ignored when using objective methods for decision selection, which makes the final decision unreasonable.

To bridge the knowledge gaps, this paper proposes a decision-making system of optimal water level in the flood season, which considers the full use of water resources, effective response measures for possible catastrophic floods and the credible decision method. In this method, firstly we use historical data and the fuzzy statistical test method to divide the flood season into multiple stages. Secondly, the maximum inflow process in the effective forecast period of flood forecast in each stage is selected, and according to this inflow process, the operating limited water level (OLWL) in the flood free period of each stage is determined based on the reservoir discharge capacity, then the operating water level range and discharge ratio are discretized. Thirdly, multi-order Monte Carlo Markov Chain (MCMC) and Monte Carlo method are used to calculate the risk rate, and the scheme set is established by the three variables of power generation benefit, discharge ratio and risk rate. Finally, the weighted Topsis method, considering subjective and objective weighting method, is applied to determine the best scheme. It can improve the operating benefit of hydropower station in the flood season and avoiding high flood control risk.

The remainder of this paper is organized as follows. Section 2 explains the establishment process and solution method of the optimal water level decision system in the flood season. Section 3 describes the application of the method to the Youjiang reservoir in

Yujiang River Basin. Section 4 presents the main results and analysis. Section 5 presents the conclusions.

2 Methodology

Figure 1 is the method frame diagram of this study. Section 2.1 describes the method of flood season segmentation. Section 2.2 establishes operating the water level and discharge scheme. Section 2.3 presents the risk analysis adopted for multi-order MCMC and Monte Carlo method. Section 2.4 explains how to make the optimal decision through weighted Topsis method.

2.1 Flood Season Segmentation

In this paper, fuzzy statistical test method is selected to divide the flood season, and the steps are as follows:

According to the daily average flow data samples over the years, take the average daily runoff of many years as the threshold, calculate the cumulative sum of the runoff exceeding
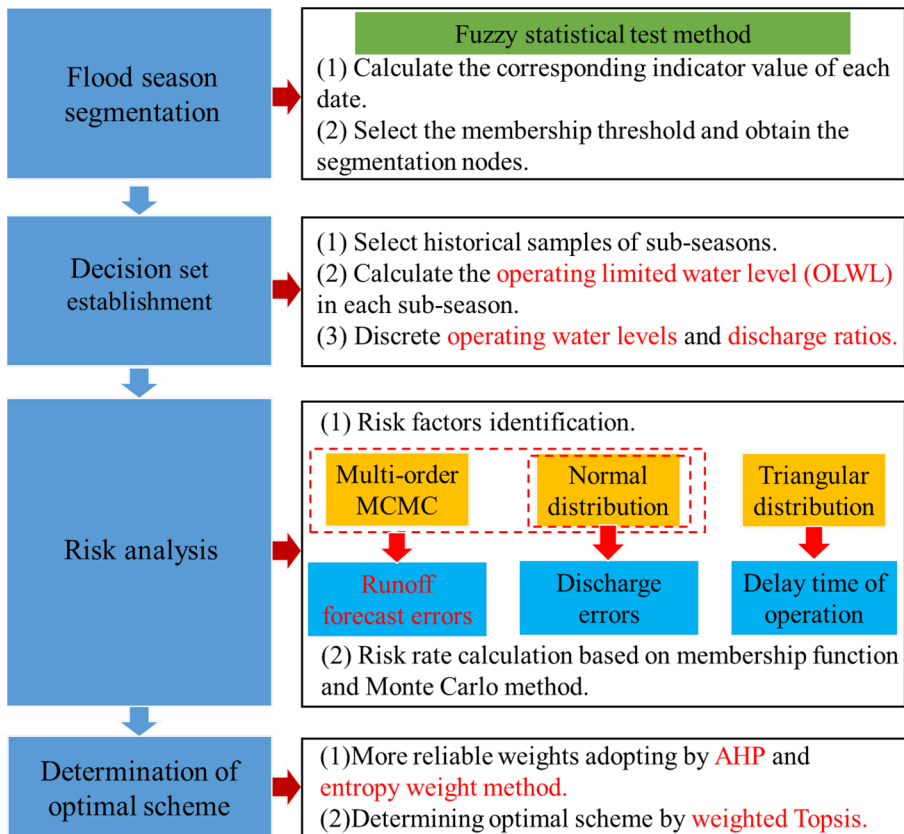

Fig. 1 Method frame diagram

the indicator threshold and the quotient of the indicator threshold in each year, divide by the total number of years, and obtain the corresponding indicator value of each date (Chen et al. 2003):

$$D_t = [\sum_{i=1}^{N} (Q_{i,t} - Q_y)/Q_y]/N \tag{1}$$

where $Q_{i,t}$ is the average daily runoff on the day t of the year i (m³/s); Q_y is the multi-year daily average flow (m³/s); N is total years.

Select an appropriate positive number as the membership threshold, and the date when the corresponding indicator value is equal to the membership threshold can be used as the segmentation node.

2.2 Establishment of the Operating Water Level and Discharge Scheme

2.2.1 Operating Limited Water Level in Each Stage

According to the historical flood data in a certain stage of the reservoir, take the excess downstream safety discharge as the flood rising point, count the water inflow data in each period of the forecast period before the rising point, and select the group with the largest total water inflow as $Q_{in} = (Q_{in,1}, Q_{in,2}, Q_{in,3}..., Q_{in,T})$, and T is the length of the forecast period.

Considering the downstream flood control safety and reservoir discharge capacity, the maximum discharge ($Q_{out,t}^{max}$) of each period in the forecast period is defined as

$$Q_{out,t}^{max} = \min(Q_{aq}, Q_{x,t}) \tag{2}$$

where Q_{aq} is the safety discharge at the downstream flood control point (m³/s), $Q_{x,t}$ is the reservoir maximum discharge in period t according to the discharge capacity (m³/s), and $Q_{x,t} = f_{zq}(Z_{t,c})$, $f_{zq}(\cdot)$ is discharge capacity curve, $Z_{t,c}$ is the initial water level in period t (m).

The water balance equation of each period is:

$$\begin{cases} V_{t,m} = V_{t,c} + (Q_{in,t} - Q_{out,t}) \times T_d \\ V_{t,c} = V_{t-1,m} \\ Z_{t,m} = f_{zv}(V_{t,m}) \\ Z_{t,c} = f_{zv}(V_{t,c}) \end{cases} \tag{3}$$

where $Z_{t,m}$ (m) and $V_{t,m}$ (m³) are the end water level and end storage in period t, $V_{t,c}$ is the initial storage in period t (m³), $Q_{out,t}$ is outflow in period t (m³/s), $f_{zv}(\cdot)$ is storage-capacity curve, T_d is the unit time (s), $t = 1 \sim T$.

Let $Q_{out,t} = Q_{out,t}^{max}$, and calculate an initial water level which brings the water level at the end of the forecast period ($Z_{T,m}$) is exactly the FLWL (Z_x) by Eq. (3). Under the premise of considering the downstream flood control safety and reservoir discharge capacity, discharging from this initial water level at the beginning of the forecast period can make the operating water level fall back to the FLWL just at the end of the forecast period, therefore this water level is recorded as the operating limited water level (OLWL) Z_O.

2.2.2 Discrete the Operating Water Level

N operating water levels are evenly dispersed based on the FLWL and the OLWL in each stage, which are recorded as: $Z = (Z_1, Z_2, ..., Z_N)$, and the upper and lower limits of each water level point are:

$$Z_x < Z_i \leq Z_O \tag{4}$$

2.2.3 Discharge Ratios Setting

To prepare for possible catastrophic floods in the future, it is necessary for pre-discharge to reserve a certain flood storage. The practical discharge can be released based on the maximum discharge ($Q_{out,t}^{\max}$) in each stage, and the discharge ratio can be defined as $\alpha = (\alpha_1, \alpha_2, ..., \alpha_M)$, whose limit constraints are:

$$0 < \alpha_i \leq 1 \tag{5}$$

At this moment the practical discharge in each period is:

$$Q_{out,t} = \alpha_i Q_{out,t}^{\max} = \alpha_i \cdot \min(Q_{aq}, Q_{x,t}) \tag{6}$$

2.3 Risk Analysis

2.3.1 Risk Factor Identification

Combined with the characteristics of reservoir flood control, three main risk factors and their probability distribution are considered in this paper.

1. Runoff forecast error

The early inflow runoff forecast mostly predicts the inflow in multiple subsequent periods at a fixed time and at a fixed interval. Therefore, when simulating the runoff forecast error, it is necessary to consider the correlation between them in different forecast time steps in the forecast period (Zhang et al. 2021). The forecast error in period j of forecast i ($e_{i,j}$) is:

$$e_{i,j} = (Q_{i,j}^y - Q_{i,j}^s)/Q_{i,j}^s \times 100\% \tag{7}$$

where $Q_{i,j}^y$ and $Q_{i,j}^s$ are the forecast flow and observed flow in period j of forecast i (m³/s).

The Markov chain is a stochastic model that describes a sequence of possible events wherein the probability of each event depends only on the state attained in previous events (Xu et al. 2021). In this paper the runoff series is simulated based on multi-order MCMC and the normal distribution of error in each period, and the steps are as follows:

1. According to the forecast error samples, the error normal distribution in period j is fitted, and $e_j \sim N(\mu_j, \sigma_j^2)$

2. The sample errors in each period are divided into different states. In this paper, the mean standard deviation classification method is used to divide the errors into five states, which are recorded as $S = (1, 2, 3, 4, 5)$, so the sample states in period j of sample i ($S_{i,j}$) are respectively:

$$\begin{cases} S_{i,j} = 1, & e_{i,j} \leq \mu_i - 1.1\sigma_i^2 \\ S_{i,j} = 2, & \mu_i - 1.1\sigma_i^2 < e_{i,j} \leq \mu_i - 0.5\sigma_i^2 \\ S_{i,j} = 3, & \mu_i - 0.5\sigma_i^2 < e_{i,j} \leq \mu_i + 0.5\sigma_i^2 \\ S_{i,j} = 4, & \mu_i + 0.5\sigma_i^2 < e_{i,j} \leq \mu_i + 1.1\sigma_i^2 \\ S_{i,j} = 5, & e_{i,j} > \mu_i + 1.1\sigma_i^2 \end{cases} \tag{8}$$

3. Transition probability matrix calculation. The i-step transition matrix (TM_j) is constructed by calculating the transition steps $f_{a,b}^{(j)}$ from one state a (time j) to another state b (time $j+1$) in the sample sequences:

$$TM_j = \begin{bmatrix} f_{1,1}^{(j)} & \cdots & \cdots & f_{r,1}^{(j)} \\ f_{1,2}^{(j)} & \cdots & \cdots & f_{r,2}^{(j)} \\ \vdots & \vdots & \vdots & \vdots \\ f_{1,r}^{(j)} & \cdots & \cdots & f_{r,r}^{(j)} \end{bmatrix} \tag{9}$$

And TPM_j can be estimated according to TM_j, as shown in Eqs. (10) and (11):

$$TPM_j = \begin{bmatrix} p_{1,1}^{(j)} & \cdots & \cdots & p_{r,1}^{(j)} \\ p_{1,2}^{(j)} & \cdots & \cdots & p_{r,2}^{(j)} \\ \vdots & \vdots & \vdots & \vdots \\ p_{1,r}^{(j)} & \cdots & \cdots & p_{r,r}^{(j)} \end{bmatrix} \tag{10}$$

$$p_{a,b}^{(j)} = \begin{cases} \dfrac{f_{a,b}^{(j)}}{\sum_{b=1}^{r} f_{a,b}^{(j)}}, & \sum_{b=1}^{r} f_{a,b}^{(j)} \neq 0 \\ 0, & \sum_{b=1}^{r} f_{a,b}^{(j)} = 0 \end{cases} \tag{11}$$

4. There are T periods in the effective forecast period of flood forecast. If the start period is j, a random number e_1 satisfying the normal distribution of errors in period j is generated, and $e_1 \sim N(\mu_j, \sigma_j^2)$. Judge the state of e_1 according to Eq. (8), subsequently the states of the relative forecast errors (S_m) are generated based on Monte Carlo method and state transition probability matrix, and $S_m = (S_1, S_2, \cdots, S_t, \cdots, S_T), S_t \in S$. We then obtain the simulation scenarios of the relative forecast errors processes $e_m = (e_1, e_2, \cdots, e_t, \cdots, e_T)$ based on uniform sampling within the error range of each state.

5. Take Q_{in} in Sect. 2.2 as the forecast runoff series, and the observed runoff of each period ($Q_{in,t}^*$) is:

$$Q_{in,t}^* = Q_{in,t}/(1 + e_t) \tag{12}$$

2. Delay time of operation

Delay time of operation comes from the steps of flood forecast and approval of superior competent department before putting operations into force. Due to difficulties to obtain its probability distribution theoretically, we thus estimated it by triangular distribution (Murtha and Janusz 1995), and the probability density function is:

$$
f(t) = \begin{cases} \frac{2(t-a)}{(b-a)(c-a)}, & a \leq t \leq c \\[2mm] \frac{2(b-t)}{(b-c)(b-a)}, & c \leq t \leq b \\[2mm] 0, & t < a, t > b \end{cases} \tag{13}
$$

where a, b and c are the minimum, maximum and possible values of scheduling delay respectively.

To ensure safety and generate electricity as much as possible before the release time ($t < t_z$, and t_z is the simulation of delay time of operation), when the inflow flow is less than the maximum power generation flow, it shall be discharged by maximum generation flow ($Q_{fd,\max}$), and if the inflow flow is greater than the maximum power generation flow, the minimum of the inflow ($Q_{in,t}$), safety discharge (Q_{aq}) and the reservoir maximum discharge ($Q_{x,t}$) shall be taken for discharge.

$$
Q_{out,t} = \begin{cases} Q_{fd,\max}, & Q_{in,t} \leq Q_{fd,\max} \\ Q_{in,t}, & Q_{fd,\max} < Q_{in,t} \leq \min(Q_{aq}, Q_{x,t}) \\ \min(Q_{aq}, Q_{x,t}), & Q_{in,t} > \min(Q_{aq}, Q_{x,t}) \end{cases} \tag{14}
$$

In order to make the risk calculation more in line with the actual operational situation, the discharge in delay time is not affected by the discharge ratio.

3. Discharge error

Discharge error mainly refers to the difference of discharge capacity caused by the error of discharge capacity curve and the operation of discharge facilities, which can be simulated by normal distribution, and the random number λ conforms to $N(1, \sigma^2)$. Variance σ^2 can be analyzed by the actual discharge data of the reservoir (Diao and Wang 2010), then the actual discharge of each period is:

$$
Q^*_{out,t} = \lambda Q_{out,t} \tag{15}
$$

2.3.2 Risk Analysis Model

Based on the pre-discharge scheme in Sect. 2.2, considering the probability that the water level of the reservoir at the end of the effective forecast period exceeds the FLWL, which may be caused by three uncertain factors: runoff prediction error q, dispatching delay time t_z and discharge capacity error x, the risk analysis model is as follows:

$$
P(Z) = P[Z^{QT}(q, t_z, x) > Z_x] \tag{16}
$$

where Z^{QT} is the water level in the end of the effective forecast period (m), which is affected by q, t_z and x.

2.3.3 Risk Model Solution

According to the water balance equation in Sect. 2.2.1, under the different conditions of operating water level point (Z_i) and discharge ratio (α_j), the water level in the end of forecast period according to the actual inflow ($Q^*_{in,t}$) and actual discharge ($Q^*_{out,t}$) in each period can be calculated, which is recorded as $Z^{QT}_{i,j}$.

Monte Carlo method (Chen et al. 2022) is used to conduct N simulations in the forecast period. Therefore, to reduce the impact of calculation errors due to water level storage capacity curve or other factors, it is necessary to determine the upper and lower floating limits of the FLWL ($Z_{x,max} and Z_{x,min}$) according to the data and actual operation. The membership function is utilized to calculate the risk rate ($P_{i,j}$) under the operating water level point (Z_i) and discharge ratio (α_j), which is:

$$\theta_n(Z^{QT}_{i,j}) = \begin{cases} 1, & Z^{QT}_{i,j} > Z_{x,max} \\ \frac{Z^{QT}_{i,j} - Z_{x,min}}{Z_{x,max} - Z_{x,min}}, & Z_{x,min} < Z^{QT}_{i,j} < Z_{x,max} \\ 0, & Z^{QT}_{i,j} < Z_{x,min} \end{cases} \tag{17}$$

$$P_{i,j} = \frac{\sum_{n=1}^{N} \theta_n(Z^{QT}_{i,j})}{N} \times 100\% \tag{18}$$

where $\theta_n(Z^{QT}_{i,j})$ is membership of $Z^{QT}_{i,j}$ in simulation n.

2.4 Determination of Optimal Scheme in Flood Free Period

The rise of water level in flood free period can bring two effects: one is the increase of the water head and the increase of power generation benefit, and the other is the risk of water level exceeding the FLWL at the end of pre-discharge period increases. Therefore, to deal with the increasingly frequent extreme flood events, this paper selects three indicators of power generation benefit, discharge ratio and risk rate to establish an index-set, thus using the weighted Topsis method to solve the optimal scheme.

2.4.1 Index-set with Power Generation Benefit, Discharge Ratio and Risk Rate

The period from the beginning of each stage of the flood season to the flood rising point is taken as the calculation period. If there is no flood in the stage, the whole stage is taken as the calculation period. The calculation method of enhanced power generation benefit (E_i) corresponding to the operating water level point (Z_i) is as follows:

$$E_i = \sum_{n=1}^{Y} (E(Z_i, n) - E(Z_x, n))/Y \tag{19}$$

where Y is total years of data, $E(Z_i, n)$ and $E(Z_x, n)$ are total power generation calculated by the runoff series of year n based on Z_i and Z_x under the same operating rules (10^8 kwh).

Therefore, an index-set with power generation benefit, discharge ratio and risk rate can be established, which includes $N \times M$ group schemes. In order to consider the flood

control demand, the membership degree $\theta_n(Z_x)$ of FLWL is calculated according to the membership function in Sect. 2.3.3 and taken as the risk threshold. The schemes with risk rate higher than the risk threshold are screened out as inferior schemes. Assuming that screened-out schemes are m groups, the remaining scheme set is $A = (a_{x,y})_{(N \times M - m) \times 3}$, which is:

$$A = \begin{bmatrix} a_{1,1} & a_{1,2} & a_{1,3} \\ a_{2,1} & a_{2,2} & a_{2,3} \\ \vdots & \vdots & \vdots \\ a_{N \times M - m,1} & a_{N \times M - m,2} & a_{N \times M - m,3} \end{bmatrix} \tag{20}$$

2.4.2 Weighted Topsis Method

Topsis normalizes the decision matrix, then multiplies the value in the column by the relative weight to determine the best and worst value in each column, and defines them as the positive ideal solution (PIS) scheme and negative ideal solution (NIS) scheme respectively. Finally, calculate the relative proximity between each scheme and the ideal solution and rank them to select the optimal scheme (Guan et al. 2022; Singaraju et al. 2022).

After establishing the scheme set, firstly normalize each index in the index-set, which is

$$r_{x,y} = \frac{a_{x,y} - x_{\min,y}}{x_{\max,y} - x_{\min,y}} \tag{21}$$

Secondly, the weight of each decision-making type is determined by the combination of subjective and objective weighting method. Given ω_y is the weight of index y, and $\sum_{y=1}^{n} \omega_y = 1$, we use the combination of analytic hierarchy process (AHP) and entropy weight method (Haghighat et al. 2021; Dong et al. 2021) to obtain ω_y, and the steps are as follows:

1. Construct the relative importance matrix B of each index type.
2. Solve the maximum eigenvalue of matrix B and the corresponding eigenvector, and transform each component of the eigenvector into the weight of each evaluation index under AHP, which is:

$$C_y = \frac{\xi_y}{\sum_{y=1}^{3} \xi_y} \tag{22}$$

3. Calculate the entropy of each index:

$$H_y = -\frac{1}{\ln(N \times M - m)} \sum_{x=1}^{N \times M - m} a_{x,y} \ln a_{x,y} \tag{23}$$

4. Calculation of entropy weight of each index according to:

$$h_y = \frac{1 - H_y}{3 - \sum\limits_{y=1}^{3} H_y} \tag{24}$$

5. The final weight of each index is obtained by combining AHP and Entropy Weight Method:

$$\omega_y = \frac{C_y \cdot h_y}{\sum\limits_{y=1}^{3} C_y \cdot h_y} \tag{25}$$

Next, PIS and NIS are determined. Given a^+ the most preferred scenarios and a^- is the least preferred scenarios, which are:

$$\begin{cases} a^+ = \{max(r_{i,1} \cdot \omega_1), \min(r_{i,2} \cdot \omega_2), \min(r_{i,3} \cdot \omega_3)\} \\ a^- = \{\min(r_{i,1} \cdot \omega_1), \max(r_{i,2} \cdot \omega_2), \max(r_{i,3} \cdot \omega_3)\} \end{cases} \tag{26}$$

Finally calculate the closeness degree (C_x^+) between each scheme and PIS:

$$C_x^+ = \frac{D_x^-}{D_x^- + D_x^+} \tag{27}$$

where D_x^+ and D_x^- are respectively the distance of scheme x from PIS and NIS. $D_x^+ = \sqrt{\sum\limits_{y=1}^{3} [\omega_y(a_{x,y} - a_y^+)]^2}$ and $D_x^- = \sqrt{\sum\limits_{y=1}^{3} [\omega_y(a_{x,y} - a_y^-)]^2}$.

Sort the schemes according to the size of closeness degree, and the scheme with the largest posting schedule is the best one.

3 Case Study

3.1 Overview of the Study Area and Data

Yujiang River is the largest tributary of the West River system in the Pearl River Basin, originating in Guangnan County, Yunnan Province. Youjiang reservoir is not only the multi-year regulating reservoir but the important flood control project in the whole Yujiang River Basin. Therefore, Youjiang reservoir was selected as a case study in this paper.

The normal level of Youjiang reservoir is 228 m, the dead level is 203 m, the installed capacity is 540 MW, the mean annual runoff is 263 m³/s, and the maximum generation flow is 692 m³/s. Moreover, Youjiang reservoir has relatively complete rainfall forecasting, runoff forecasting system and real-time operation system, in which runoff forecasting adopts rolling forecasting mode: Once a day, hour by hour for the next seven days, and runoff forecasting accuracy within one day meets the requirements of use and can be used as the effective forecast period of flood forecast, thus the forecast period is 24 h.
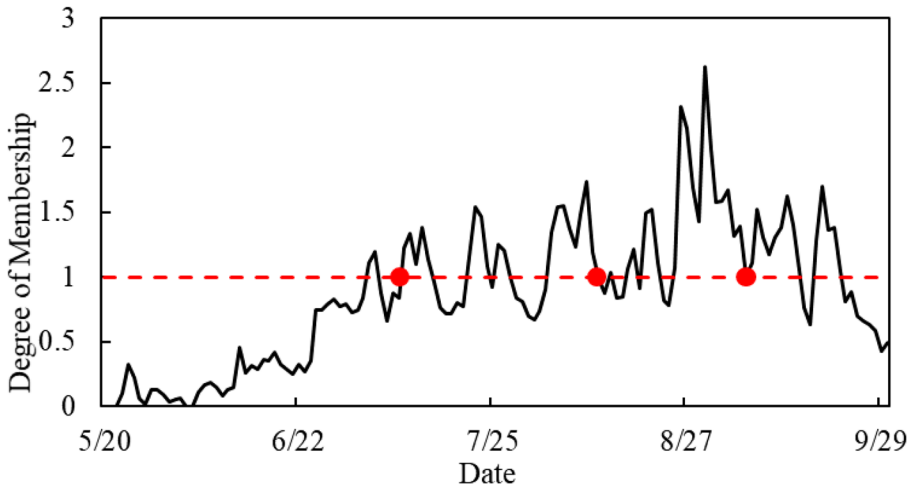
Fig. 2 The result of flood season segmentation by fuzzy statistical test method

3.2 Result of Flood Season Segmentation

The beginning and ending time of the flood season are 20 May and 30 September respectively. The result of flood season segmentation by fuzzy statistical test method is shown in Fig. 2, where the black line is the membership function, the red line is the selected membership threshold, and the red dot is the intersection of the threshold and the membership function, representing the segmentation node.

Furthermore, the segmentation is determined on the basis of fuzzy statistical test method result by using ten days period for the convenience of operations. The dates of segmentation nodes are 10 July, 10 August and 31 August respectively.

## 3.3 Calculation of Operating Water Level in Flood Free Period

Flood season of Youjiang station is divided into 4 stages. According to the design flood data and the actual operation of Youjiang station, FLWL in each stage and the safe discharge are determined, therefore, the operating limited water level in stage can be obtained

**Table 1** The FLWL, safe discharge, OLWL and discrete accuracy of each stage

	Unit	1st stage	2nd stage	3rd stage	4th stage
Segmentation	/	20 May.-10 Jul	11 Jul.- 10 Aug	11 Aug.- 31 Aug	1 Sept.- 30 Sept
FLWL	m	214	219.7	222.3	228
Safety discharge	m^3/s	2000			
OLWL	m	214.8	220	223	/
Discretization precision	m	0.1	0.05	0.1	/

and discretized according to the calculation formula of Sect. 2.2. The FLWL, safety discharge, OLWL and discrete accuracy of each stage are shown in Table 1.
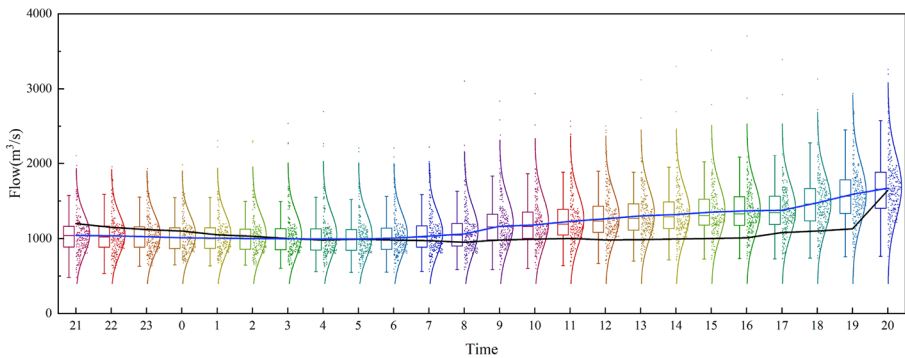
The FLWL in the fourth stage is equal to the normal water level, thus it is not considered to raise the operating water level during the fourth stage.
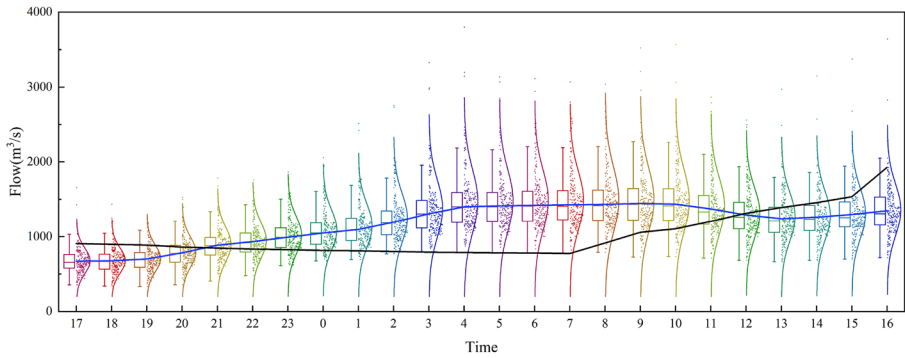
(a) the first stage
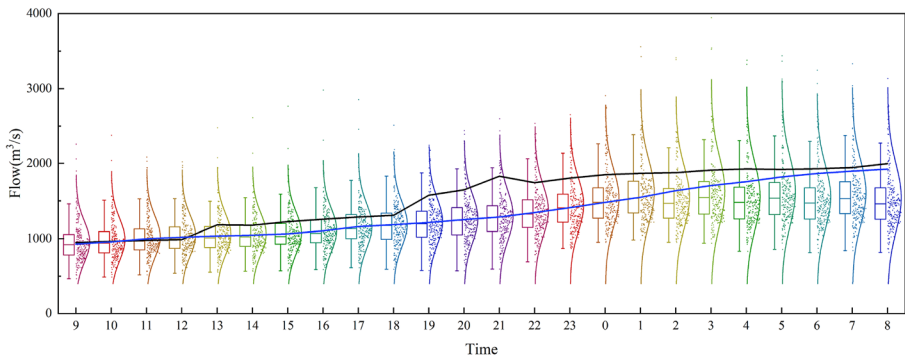
(b) the second stage

(c) the third stage

Fig. 3 the forecast runoff, observed runoff and time-interval error distribution selected in each period

3.4 Risk Factor Identification

The normal distribution curves of errors in each period are fitted according to the forecast data and observed data. And the forecast runoff, observed runoff and time-interval error distribution selected in each period are shown in Fig. 3. Figure 3a–c belong to the first, second and third stage respectively. The black line is the observed runoff and the blue line is the forecast runoff. The color box diagram represents the normal distribution of errors in
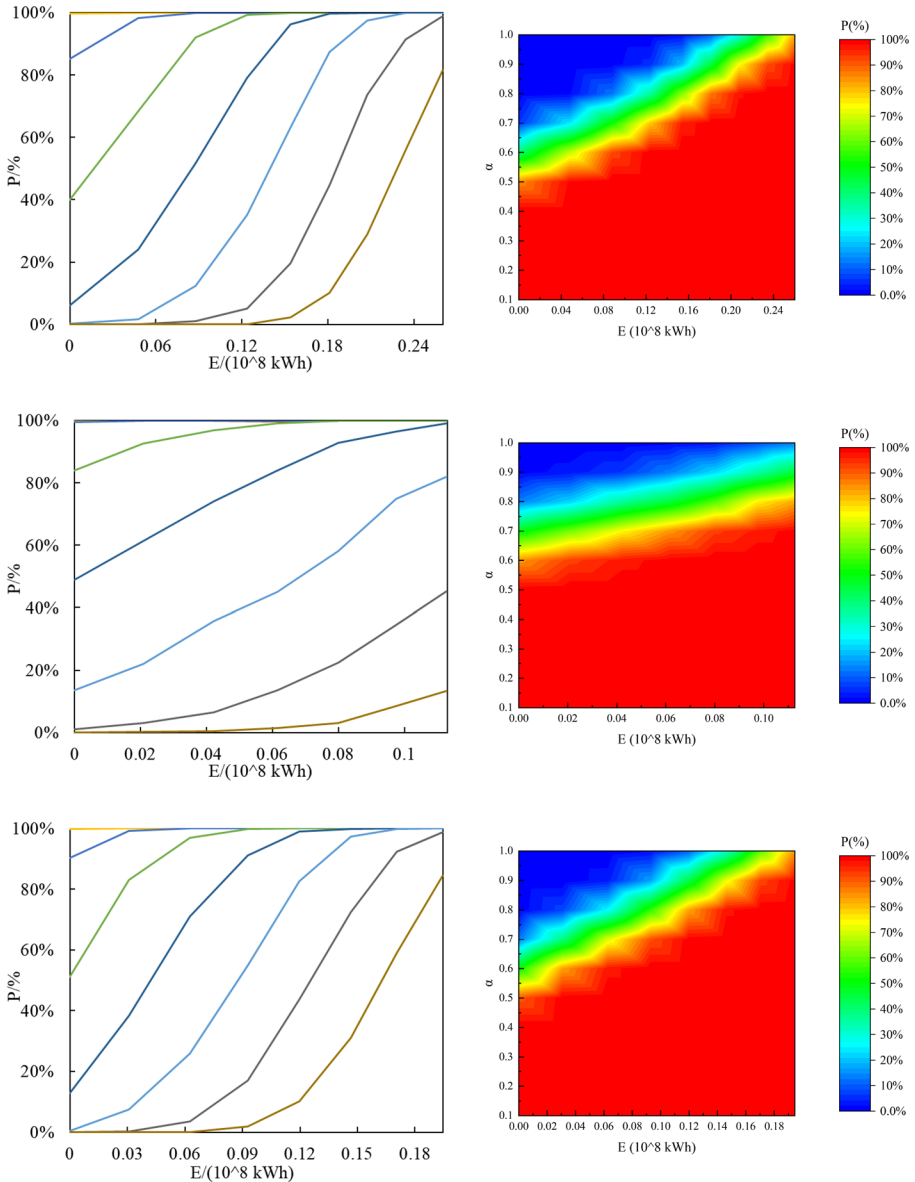

Fig. 4 Relationship between power generation benefit, discharge ratio and risk rate of each stage

each period. The absolute relative error value of the total water volume of the third period forecast data is less than 20%, therefore these can be used as calculation samples of risk rates for each stage.

According to the operation data of the power station, the discharge error approximately meets $\lambda \sim N(1, 0.05^2)$. Youjiang reservoir has sound regulation and forecast system, and the minimum, most likely and maximum values of delay time of operation are determined as 0 h, 0 h and 1 h respectively according to the experience of operation experts. The trigonometric distribution function is:

$$f(t) = \begin{cases} 2(1 - t), & 0 \le t \le 1 \\ 0, & t < 0, t > 1 \end{cases}$$

3.5 Calculation of Risk Rate and Determination of Optimal Scheme

Set discharge ratio $\alpha = (0.1, 0.2, ..., 1)$, moreover, according to the error of water level storage capacity curve of Youjiang River, wind and waves and other factors, the fluctuation range of the FLWL in each period is set as $(Z_x - 0.1, Z_x + 0.1)$, and the maximum number of Monte Carlo simulation is 5000. Based on the risk rate calculation method in Sect. 2.3, the risk rate of each operating water level point in each period under different discharge ratio is calculated.

According to the calculation method of power generation benefit in Sect. 2.4.1, the operating water level is transformed into power generation benefit. The results of each period are shown in Fig. 4, in which P is the risk rate, E is the power generation benefit and α is the discharge ratio. It can be seen from the figure that the risk rate is in direct proportion to the benefit and in inverse proportion to the discharge ratio.

Combined with the membership function of water level, the risk threshold of each stage is 0.5, therefore the index-set of each stage is established and solved by Sect. 2.4 weighted Topsis method after the schemes at risk rate of more than 50% are screened. The weight calculation and the optimal scheme of each stage are shown in Table 2. H represents the increase water head corresponding to power generation benefit E.

4 Discussion

Furthermore, to prove that the optimal scheme is not only reduces water abandonment, but also improves the operational benefit of the power station, and avoids the high risk caused by water level rise, we compare it with the original scheme which maintains the

Table 2 The weight calculation and the optimal scheme of each stage

	Unit of the optimal scheme	1st stage		2nd stage		3rd stage	
		Weight	Optimal scheme	Weight	Optimal scheme	Weight	Optimal scheme
H	m	/	0.4	/	0.1	/	0.2
E	10^8 kWh	0.41	0.15	0.22	0.04	0.23	0.06
α	/	0.37	0.9	0.31	0.9	0.37	0.9
P	%	0.22	20	0.47	6	0.50	4

Table 3 The benefit increased and abandoned water reduced in the flood season of each year

| Year	Power generation benefit				Abandoned water			
	Original scheme	Optimal scheme	Increase amount	Percentage increased	Original scheme	Optimal scheme	Reduction amount	Percentage reduction
	10^8 kWh	10^8 kWh	10^8 kWh	%	10^8 m^3	10^8 m^3	10^8 m^3	%
2013	4.20	4.29	0.09	2.14	0	0	0	0
2014	7.75	7.86	0.11	1.42	1.22	1.13	0.09	7.38
2015	8.43	8.68	0.25	2.97	4.17	3.43	0.74	17.75
2016	4.48	4.57	0.09	2.01	0.03	0	0.03	100
2017	8.91	9.05	0.14	1.57	7.38	6.98	0.40	5.42
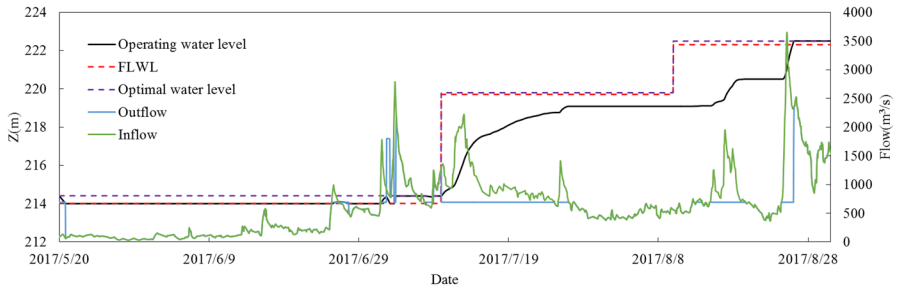
Fig. 5 The operation process in the flood season in 2017

water level at the FLWL. Based on the flood season operation rules of Youjiang River, the runoff of Youjiang River in the flood season from 2013 to 2017 is used for inspection, and the increase of benefit and decrease of abandoned water in each year by the optimal scheme is shown in Table 3.

The operation process in the flood season in 2017 is shown in Fig. 5, in which the black line represents the water level process, the green line represents the inflow process, the blue line represents the outflow process, the red dotted line represents FLWLs, and the purple dotted line represents the raised water level. There are three floods in this flood season, of which the first needs pre-discharge, and risk rate in the optimal and original scheme are 6% and 1% respectively. Moreover, compared with the original scheme, the power generation benefit of this method is increased by 1.57% and the abandoned water is reduced by 5.42% in this flood season.

In addition, there is no need to surplus water released from the reservoir if there is no flood, which is conducive to the storage of the reservoir after the flood season.

5 Conclusions

Long-term operation of the reservoir at the flood limit water level (FLWL) in the flood season is not conducive to the exertion of the comprehensive benefits of the reservoir, especially in the flood free period. To make full use of the water resources and avoid the risk of flooding due to extreme events, this paper proposes a decision-making system of optimal water level in the flood season, which considers the full utilization of resources, effective response measures for possible catastrophic floods and the credible decision method. The method is applied to Youjiang reservoir in Yujiang River Basin, and the following conclusions are drawn:

1. Combined with the discharge in the forecast period, the reservoir operating water level has a certain raising space in the flood free period, which can effectively reduce the waste of resources.
2. The multi-order MCMC method effectively reflects the relationship between adjacent periods of runoff forecast error, and its simulation process is closer to the reality.

3. Topsis with the combination of AHP and entropy weight method can fully consider the characteristics of power generation benefit, discharge ratio and risk rate, and it is effective to select the optimal solution from the set of non-inferior schemes.

In the future research, a variety of normalization and weight methods can be used to solve the scheme, thus realizing the rapid determination and application of the scheme under the different needs of decision makers.

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Declarations

Conflicts of Interest/Competing Interests The author has no conflicts to declare that are relevant to the content of this article.

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Authors and Affiliations

Zhenyu Mu[1] · Xueshan Ai[1,2] · Jie Ding[1] · Kui Huang[3] · Senlin Chen[1] · Jiajun Guo[1] · Zuo Dong[1]

✉ Xueshan Ai
xsai@whu.edu.cn

1   State Key Labaratory of Water Resources and Hydropower Engineering Science, Wuhan University, Wuhan 430072, China

2   Hubei Urban Construction Vocational and Technological College, Wuhan University, Wuhan 430205, China

3   Guangxi Electric Power Dispatching and Control Center, Nanning 530023, China