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ORIGINAL PAPER

A two-stage method of quantitative flood risk analysis for reservoir real-time operation using ensemble-based hydrologic forecasts

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Abstract Quantitative analysis of the risk for reservoir real-time operation is a hard task owing to the difficulty of accurate description of inflow uncertainties. The ensemble-based hydrologic forecasts directly depict the inflows not only the marginal distributions but also their persistence via scenarios. This motivates us to analyze the reservoir real-time operating risk with ensemble-based hydrologic forecasts as inputs. A method is developed by using the forecast horizon point to divide the future time into two stages, the forecast lead-time and the unpredicted time. The risk within the forecast lead-time is computed based on counting the failure number of forecast scenarios, and the risk in the unpredicted time is estimated using the reservoir routing with the design flood hydrographs. As a result, a two-stage risk analysis method is set up to quantify the entire flood risks by defining the ratio of the number of failure scenarios (excessive the critical value) to the total scenarios number. The China's Three Gorges Reservoir is selected as a case study, where the parameter and precipitation uncertainties are conducted to produce ensemble-based hydrologic forecasts. Two reservoir operation schemes, the historical operated and scenario optimization, are evaluated with the flood risks and hydropower profits analysis. The derived risk, which units with yearly scale, associates with the flood protection standards (described with return periods) that can be used as the acceptable level to operate reservoir. With the 2010 flood, it is found that the proposed method can greatly improve the hydropower generation with acceptable flood risks.

Keywords Reservoir operation · Ensemble-based hydrologic forecasts · Risk analysis · Multi-objective · Scenario optimization

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1 Introduction

Reservoirs, which have contributed a significant role in the development of human civilization, such as flood control, hydropower, and water supply for municipal, industrial, and agricultural uses, are one of the most efficient measures for the integrated water resources development and management (Yeh 1985; Guo et al. 2004; Labadie 2004). Although the effective real-time operation of reservoirs have been widely studied and summarized (Yeh 1985; Labadie 2004); it is still a difficult task due to the gap between theories and practices Wurbs (1993), where the uncertainty caused by stochastic inflows is one of the most difficulties to tackle.

To understand the uncertainty involved in reservoir real-time operation, quantitative risk analysis have been widely studied and applied to reservoir decision-making (e.g., Xu et al. 1997; Apel et al. 2006). By controlling the risk under an acceptable level, the reservoir's functions can be maximized, and a reasonable decision can be then made based on the trade-off between the risks and profits (e.g., Simonovic and Marino 1980; Datta and Houck 1984; Reznicek and Cheng 1991; Sreenivasan and Vedula 1996; Ouarda and Labadie 2001; Pianosi and Soncini-Sessa 2009). As a result, the quantitative risk analysis has become the key issue for reservoir real-time operation.

The risk is originally measured by both the probability of the event and the seriousness of the consequences (Plate 2002), and only the probability is taken into account in this study. In this case, the risk of reservoir operation can be defined with the probability in various ways, such as the reservoir water level above a critical level (e.g., the risk of dam overtopping), and the water release more than a critical discharge (Tung and Mays 1981). Marien (1984) analyzed the reservoir risk by giving a set of inflow scenarios, which also used by Kelman et al. (1989) to determine the optimal flood control volumes. Marien et al. (1994) extended the method for flood control of multipurpose multi-reservoir systems. Turgeon (2005) determined the optimal daily operating policy of a small reservoir subject to yearly probabilistic constraints on floods and shortages. Kuo et al. (2007) used five methods, including the Rosenblueth's point estimation method, the Harr's point estimation method, Monte Carlo simulation, Latin hypercube sampling, and the mean-value first-order second-moment method, to assess the reservoir dam overtopping risk. It was found that the Monte Carlo method is still the most reliable method, since the quantitative risk analysis problem is difficult due to the persistence of the inflows (Turgeon 2005). Therefore, the Monte Carlo method also benchmarks for reservoir risk analysis owing to the complexity of accuracy description of the inflow distribution, the model and parameter uncertainties. However, the Monte Carlo method is often unable to apply to real reservoir operation risk analysis owing to the heavy computation burden.

On the other hand, the ensemble-based forecasts have the ability of describing the inflow uncertainty directly, because they easily depict the inflows not only the marginal distributions but also their persistence via scenarios. The ensemble streamflow prediction is a general and popular forecast technique for the real reservoir operation (Alemu et al. 2011), which has been well literature by Cloke and Pappenberger (2009). It is a natural idea that the ensemble-based hydrologic forecasts (forecast scenarios) can be directly input to the reservoir operation model and used into risk analysis. Based on the above idea, risk analysis for reservoir real-time operation is conducted by using the ensemble-based hydrologic forecasts in this study, which has seldom been addressed in the literature.

The remainder of this paper is organized as follows. In Sect. 2, a risk analysis model is presented, which is driven by inputting an ensemble-based hydrologic forecast. Section 3 deals with a case study of the Three Gorges Reservoir (TGR). Finally, conclusions are given in Sect. 4.

2 Methodalogy

A scenario is defined here as a streamflow hydrograph (Faber and Stedinger 2001). Based on the ensemble forecasts with m members, the risk is defined as the frequency of the failure number of members k, i.e., $\frac{k}{m}$. Two flood risks, either the release discharge or the reservoir water level (elevation) is greater than a critical value, are considered to assess the risk of reservoir operation.

As shown in Fig. 1, the future beyond the current time period is divided into two stages by the forecast horizon point: the forecast lead-time (forecast horizon) and the consequent time period, where the latter is called as the unpredicted time owing to the difficult of streamflow prediction. Based on the above two-stage, the entire risk consists of two dependent items: one is the risk within the forecast lead-time, which can be computed based on counting the failure numbers of scenarios; the other is the risk in the unpredicted time, although which is difficult to calculate due to floods after the lead-time, but it can be estimated using the statistical information, i.e., the design flood hydrographs. Thus, the risk in the unpredicted time is estimated using reservoir routing with the design flood hydrographs in this study. It is notable that the initial water level of the reservoir routing, i.e., the time of forecast horizon point, should be begin with the reservoir end water level of stage one (reservoir routing with forecasts). A novel method presented in this study is that not only the failure probability within the forecast lead-time is taken into account, but also the risk in the unpredicted time is considered.

2.1 Reservoir routing model

The basic reservoir routing model is based on the mass balance equation (Loucks et al. 2005), i.e.,

$$V_{t+1} = V_t + \left(\frac{I_t + I_{t+1}}{2} - \frac{R_t + R_{t+1}}{2}\right)\Delta t - e_t,$$
$$t = t_1, t_2, \ldots, t_{n-1} \qquad (1)$$

where I_t, R_t and V_t denote reservoir inflow, release and storage at time period t, respectively. e_t denotes reservoir losses during time period t, which is often ignored. Δt is the time interval.

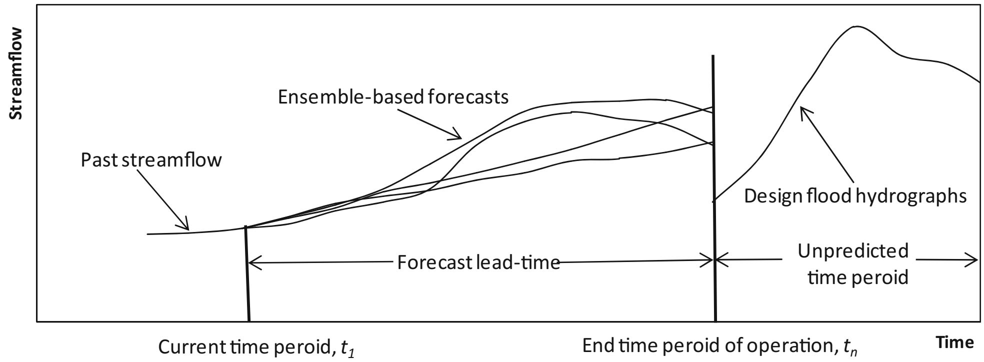


Fig. 1 Framework of the reservoir risk analysis using two stages within the forecast lead-time and the unpredicted time period

The constraints are expressed as follows:

$$R_{min} \leq R_t \leq R_{max} \tag{2}$$

$$V_{min} \leq V_t \leq V_{max} \tag{3}$$

where R_{min} denotes the reservoir minimum release for other purposes, such as environment and navigation, and R_{max} denotes the reservoir maximum release for the downstream safety and spillways capacity. V_{min} denotes allowed reservoir minimum storage, which is often the storage corresponding to the dead water level. V_{max} denotes storage capacity of reservoir, which is often the storage corresponding to the normal water level.

Based upon the reservoir routing model and ensemble-based forecasts, two operation models can be set up as follows:

(1) *Release control model* When the reservoir releases have been pre-determined, the corresponding water levels are simulated for each forecast scenario, respectively. In this case, there is only one scheme of the reservoir releases and m scenarios of the reservoir water levels.
(2) *Water level control model* The reservoir water levels have been pre-determined, thus the corresponding reservoir releases can be simulated for each forecast scenario, respectively.

2.2 Risk within forecast lead-time

The release discharge or the reservoir water level (evaluation), which is greater than a critical value, is considered to assess the risk of reservoir operation. The risk within forecast lead-time is calculated as follows:

(1) The risk of the downstream.

$$R_{1,down} = \text{Prob}(R > Q_c) = \frac{\sum_{i=1}^{m} \#(R_{i,t} > Q_c, \quad \forall t = t_1, t_2, \ldots, t_n)}{m} \tag{4}$$

where $\#(R_{i,t} > Q_c, \forall t = t_1, t_2, \ldots, t_n) = \begin{cases} 1 & R_{i,t} > Q_c, \forall t = t_1, t_2, \ldots, t_n \\ 0 & otherwise \end{cases}$ is a one-zero variable for scenario i, i.e., the value is equal to one if any release is greater than the critical value, otherwise it is zero. It should be noted that the value is also set to one even failure times more than once. $\sum_{i=1}^{m} \#(R_{i,t} > Q_c, \quad \forall t = t_1, t_2, \ldots, t_n)$ indicates the number of scenarios where at least one of release discharges is greater than the critical value Q_c, and hence the risk within forecast lead-time can be given by counting the release failure number among m scenarios.

(2) The risk of the reservoir upstream is due to the flood merge even dam overtopping.

$$R_{1,up} = \text{Prob}(Z > Z_c) = \frac{\sum_{i=1}^{m} \#(Z_{i,t} > Z_c, \forall \quad t = t_1, t_2, \ldots, t_n)}{m} \tag{5}$$

where $\sum_{i=1}^{m} \#(Z_{i,t} > Z_c, \quad \forall t = t_1, t_2, \ldots, t_n)$ indicates the number of scenarios where at least one of reservoir water levels is more than the critical value Z_c, that is the failure number of water levels.

2.3 Risk in unpredicted time

Except for the risk within the forecast lead-time, the consequent flood risk in the unpredicted time should be taken into account. In this case, the reservoir's design flood hydrographs are used to depict the associated risk.

Risk $R_{2,down}$ is defined as the probability that the reservoir release exceeds the critical value Q_c if the flood events (design hydrographs) occur at time t_n (Fig. 1). Assuming that the water level Z_{i,t_n} at time t_n is uncorrelated with the forthcoming flood, the risk can be estimated by Li et al. (2010):

$$R_{2,down} = \sum_{i=1}^{m} R_{down}(Z_{i,t_n})P(Z_{i,t_n}) = \frac{\sum_{i=1}^{m} R_{down}(Z_{i,t_n})}{m} \tag{6}$$

where Z_{i,t_n} is water level at time t for scenario i, $P(Z_{i,t_n})$ is the probability of end water level reach to Z_{i,t_n} that is often set as equal probability, and $R_{down}(Z_{i,t_n})$ is the frequency of forthcoming flood when the storage level is Z_{i,t_n}, and it can be derived by reservoir routing (flood regulating calculation). For example, starting from the flood limit water level, the risk encountered with the 100-year design flood hydrograph is equal to 0.01.

Similarly, the risk of the unpredicted time for the upstream can be expressed as follow:

$$R_{2,up} = \sum_{i=1}^{m} R_{up}(Z_{i,t_n})P(Z_{i,t_n}) = \frac{\sum_{i=1}^{m} R_{up}(Z_{i,t_n})}{m} \tag{7}$$

2.4 Entire risk

The risks within the forecast lead-time and in the unpredicted time are statistical related. Since the entire risk R_{down} is the probability of the failure number for all scenarios, it can be calculated as follow:

$$R_{down} = R_{1,down} + P(R_{2,down}|\bar{R}_{1,down}) = \frac{\sum_{i=1,i\in T}^{m} \#(R_{i,t} > Q_c, \quad \forall\, t = t_1, t_2, \ldots, t_n) + \sum_{i=1,i\notin T}^{m} R_{down}(Z_{i,t_n})}{m} \tag{8}$$

where T means the set of scenarios where at least one of the release discharge is greater than the critical value. The above estimated risk equation is based on the inflow scenarios, and the entire risk R_{down} is the ratio of failure number to all scenarios number.

Similarly, the entire risk R_{up} can be calculated as follow:

$$R_{up} = \frac{\sum_{i=1,i\in T}^{m} \#(Z_{i,t} > Z_c, \quad \forall\, t = t_1, t_2, ..., t_n) + \sum_{i=1,i\notin T}^{m} R_{up}(Z_{i,t_n})}{m} \tag{9}$$

Clearly, the proposed risk is a yearly scale and related to the flood protection standard, which is described with return period. The flood protection standard is therefore used as the acceptable risk.

3 Case study

3.1 The Three Gorges Reservoir

The TGR is a vital project for water resources development of China's largest river, the Yangtze River (Fig. 2). The TGR receives inflow from a 4.5×10^3-km-long channel with a contributing drainage area of 10^6 km^2. The mean annual runoff at the dam site is 4.51×10^{11} m^3. Currently, the TGR is the largest multipurpose hydro-development project ever built. The benefits of the TGR include flood control, power generation and improved navigation. With a flood storage capacity of 2.215×10^{11} m^3, the TGR plays a very important role in flood control of the Yangtze River. The dam has 32 sets of 700 MW hydraulic turbo generators, i.e. 22,400 MW in total installed capacity. The TGR supplies a large proportion of its electricity to eastern and central China.

As shown in Fig. 3, the risk analysis involves three procedures as follows.

(1) *Generation of ensemble-based forecasts* Since both the probabilistic forecasting and the ensemble streamflow prediction (ESP) are expressed as the ensemble-based forecasts, we only use the probabilistic forecast with parameter and precipitation uncertainties to produce the inflow scenarios, for a demonstration. No difference between the ESP and probabilistic forecasting to the reservoir operator since both of them are depicted as a lot of scenarios.

(2) *Reservoir simulation with scenarios* The reservoir operation is implemented by inputting ensemble-based forecasts, and then a set of operation results is obtained by using either reservoir release of water level control models.

(3) *Flood risks evaluation and controlling* Based upon these operation scenarios, the reservoir operation risks can be calculated and evaluated.

3.2 Ensemble-based forecasts

3.2.1 Hydrologic model

The inflow of TGR consists of three components, the main upstream inflow (Cuntan gage station), the tributary inflow from the Wu River (Wulong gage station), and the rainfall runoff from the TGR intervening basin (Fig. 2). The intervening basin has a catchment area of 55,907 km^2, about 5.6 % of the TGR upstream Yangtze River basin. Over the entire intervening basin, there are 40 rainfall gauged stations and 2 hydrological stations (Cuntan and Wulong), which control the upstream inflow and tributary inflow, respectively.

The observed streamflows of Cuntan and Wulong, and the rainfall data in the intervening basin are used for the hydrologic forecasting. With the time interval of 6 hour, data of flood season (from June to September) from 2003 to 2010 is used, where 2003–2007 is the calibration period, and the data of 2008 to 2010 is used for validation.

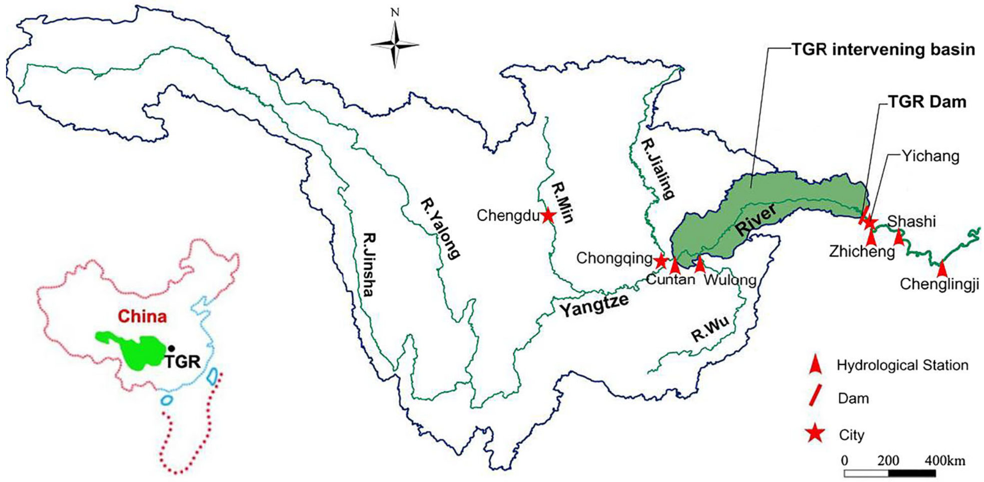


Fig. 2 The location of the TGR basin in China

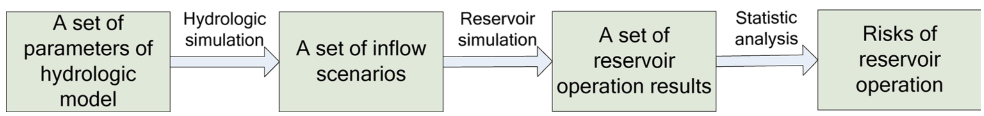


Fig. 3 Sketch of the reservoir risk analysis using ensemble-based forecasts

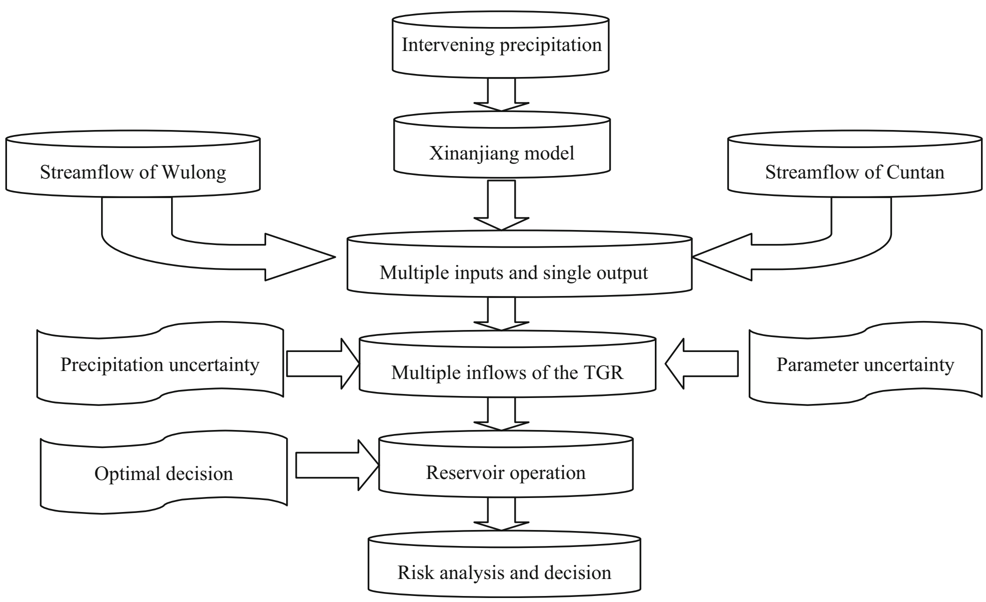


Fig. 4 Flowchart of the TGR ensemble-based forecasts generation using the Bayesian method

Figure 4 demonstrates the flowchart of the probabilistic hydrologic forecasting for the TGR. The hydrologic simulation is implemented by using a multiple inputs and single output model (MISO) Liang et al. (1992), where the streamflows of Wulong and Cuntan stations are used to depict the upstream and tributary flows respectively. The Xinanjiang model Zhao (1992), a conceptual rainfall-runoff model, is set up to model rainfall-runoff relationship of the intervening basin.

The formulation of the MISO for the TGR is expressed as follow Li et al. (2010):

$$\hat{I}_t = \sum_{j=1}^{m_1} x^{(1)}_{t-j+1} h_1(\Delta t, j) + \sum_{j=1}^{m_2} x^{(2)}_{t-j+1} h_2(\Delta t, j) + f(P_t, P_{t-1}, P_{t-2}, \cdots) \tag{10}$$

where $\hat{I}_t$ is the forecasted inflow of the TGR at time t; $x_t^{(1)}$ and $x_t^{(2)}$ are the inflows of the Cuntan and Wulong gage stations at time t, respectively; m_1 and m_2 are the memory lengths, respectively; P_t is the mean rainfall of the intervening basin during time t; $f(\cdot)$ denotes the Xinanjiang model, the evaporation is ignored since it limited affect the floods; $h_1(\Delta t, j)$ and $h_2(\Delta t, j)$ are impulse responses that can be calculated by Nash model.

$$h_i(j) = \frac{1}{K_i \Gamma(n_i)} e^{-(j/K_i)} (j/K_i)^{n-1} \quad (11)$$

$$S_i(j) = \int_0^j \frac{1}{K_i \Gamma(n_i)} e^{-(\tau/K_i)} (\tau/K_i)^{n_i - 1} d\tau \quad (12)$$

$$h_i(\Delta t, j) = [S_i(j) - S_i(j - \Delta t)]/\Delta t \quad (13)$$

where $\Gamma(n_i)$ is the Gamma function; n_i (the number of linear reservoirs) and K_i (the common storage coefficient) are the parameters of Nash model.

Finally, 19 parameters, including 15 parameters of the Xinanjiang model, and four parameters of the Nash models that simulate streamflow from Wulong and Cuntan to the TGR respectively, are implemented for the uncertainty analysis.

3.2.2 *Uncertainties implementation*

Bayesian inference is an approach to statistics in which all forms of uncertainty are expressed in terms of probability. With the development and application on watershed models for the analysis of hydrologic systems, Bayesian uncertainty forecasting becomes a popular technique for hydrologic study (Beven and Binley 1992; Vrugt et al. 2003; Pappenberger and Beven 2006). Beven and Binley (1992) proposed a pseudo-Bayesian framework, namely generalized likelihood uncertainty estimation (GLUE), which is easy of implementation, to produce probabilistic forecasting. Based on GLUE, Lin et al. (2014) proposed the discharge criterion of interior gauge station to select the behavioral parameters and then reduce the uncertainty. Vrugt et al. (2003) used the Monte Carlo Markov Chain (MCMC) method to update the estimating covariance values and then derived the posterior target distribution. After that, Vrugt and Robinson (2007) presented the simultaneous optimization and data assimilation method, which combined the SCEM-UA algorithm with an ensemble Kalman filter. Indeed, uncertainty analysis of flood forecasting involves the quantification of uncertainty in the model inputs, parameters, structure, and observations Liu and Gupta (2007). We only discuss the parameter uncertainty for the hydrologic model in this study, and this simplicity does not cause significant loss for the proposed reservoir operation model. An advanced MCMC method, the adaptive Metropolis (Haario et al. 2001; Marshall et al. 2004; Smith and Marshall 2008), is used to produce a number of samples (scenarios).

3.2.3 *Measurement criterions*

Two measurement criterions are used to evaluate the performance of the MISO: the Nash–Sutcliffe model efficiency index R^2 (Nash and Sutcliffe 1970) and the mean relative error of the volumetric (RE). They are expressed as follows:

$$R^2 = \left[1 - \frac{\sum (Q_t - \hat{Q}_t)^2}{\sum (Q_t - \bar{Q})^2}\right] \times 100\ \% \quad (14)$$

$$RE = \frac{\sum (Q_t - \hat{Q}_t)}{\sum Q_t} \times 100\ \% \quad (15)$$

where Q_t and $\hat{Q}_t$ are the observed and simulated discharges at time t, respectively, and $\bar{Q}$ is the mean value of Q_t during calibration or validation periods.

The R^2 and RE for the median values of the 90 % prediction interval are 0.96 and 0.02 for the calibration period, and are 0.94 and -0.01 for the validation period. Figure 5 demonstrates the results of the MISO simulation using parameter uncertainty analysis. With the streamflow simulation in 2004, it shows that a number of inflow scenarios could be produced by considering the parameter uncertainty. These scenarios not only describe the marginal distribution of the observed streamflow, but also reflect their persistence.

One of the top five observed floods on the TGR, the 2010 flood is used to evaluate the reservoir real-time operation. Figure 6 shows the results of the quantified precipitation forecast (implemented and published by the Yangtze River Water Resources Commission), which has three key values, the maximum, the minimum and the recommend precipitation. The uncertainty forecasts of the Cuntan and Wulong streamflows are implemented and published by the Yangtze River Water Resources Commission. Figure 7 shows the ensemble forecasts that is produced with the uncertainties of both the parameters and precipitation (Pappenberger et al. 2005).

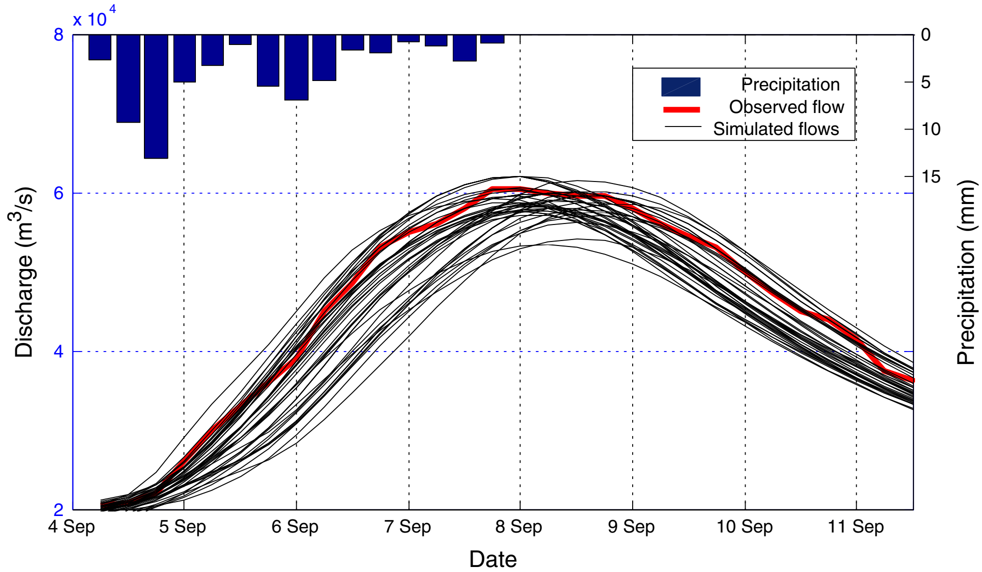
3.3 Two schemes for reservoir operation

Two schemes, the historical operation and the optimal one, are compared as follows.

3.3.1 *Operated operation*

Figure 8 shows the historical (operated) operation of the TGR for the 2010 flood. The maximum streamflow

Fig. 5 Streamflow simulation of the TGR in 2004 by considering the parameter uncertainty of hydrologic model



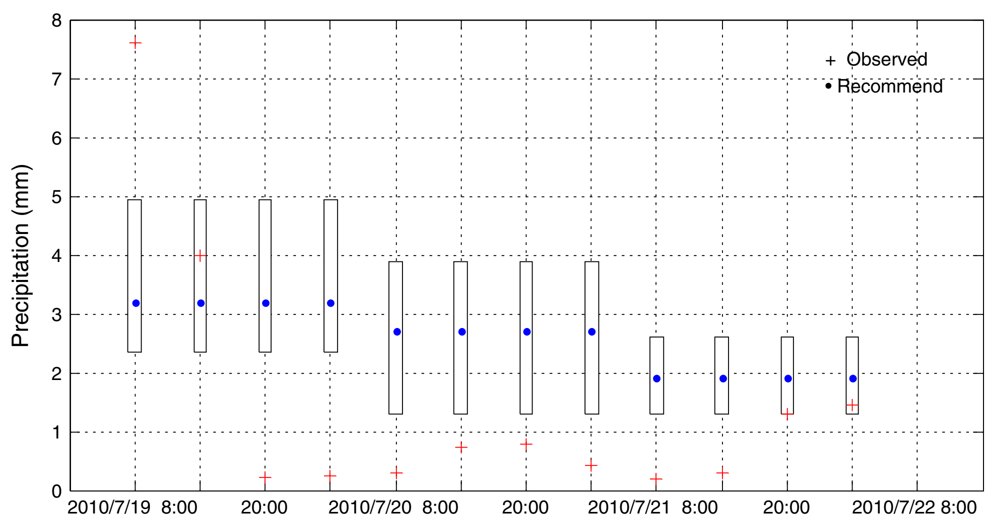


Fig. 6 Predicted precipitation at 2010 July 19 with 3 days lead-time

reached 70,000 m^3/s on 21st, July. The total hydropower generation is 1.44 billion kWh with the end water level of 152.41 m.

3.3.2 Scenario-based reservoir operation

Since the inflow scenarios are used, the optimization approaches such as scenario optimization (Dembo 1991), sampling stochastic dynamic programming (SSDP) (Kelman et al. 1990), or scenario trees Watkins et al. (2000) can be used to find the optimal operation. The SSDP is chosen to implement the scenario-based reservoir operation. The SSDP formulates a deterministic problem Liu et al. (2011) for each scenario, and forces it shared by two or more scenarios. It should be noted that the SSDP could be improved and accelerated by using analytical probability density functions (PDFs), with the idea of Wang and Tartakovsky (2012).

The optimization objective functions are expressed as follows:

(1) Minimization of the reservoir maximum water level, which can be described as

$$F_1 = \min \max_{t=t_1,t_2,\ldots,t_n} V_t \quad \Leftrightarrow \quad F_1 = \min \sum_{t=t_1}^{t_n} V_t^2 \tag{16}$$

(2) The downstream flood control objective is to minimize the maximum discharge, which can be described as follow:

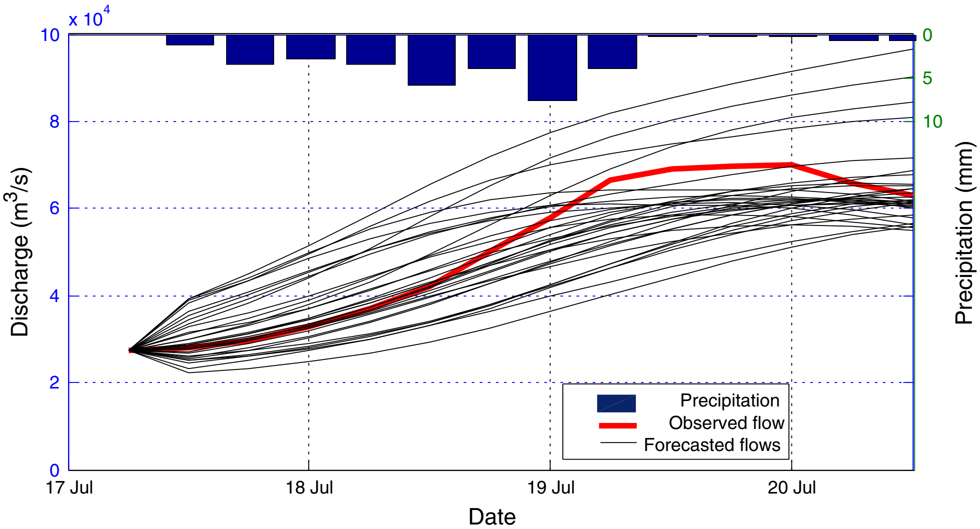
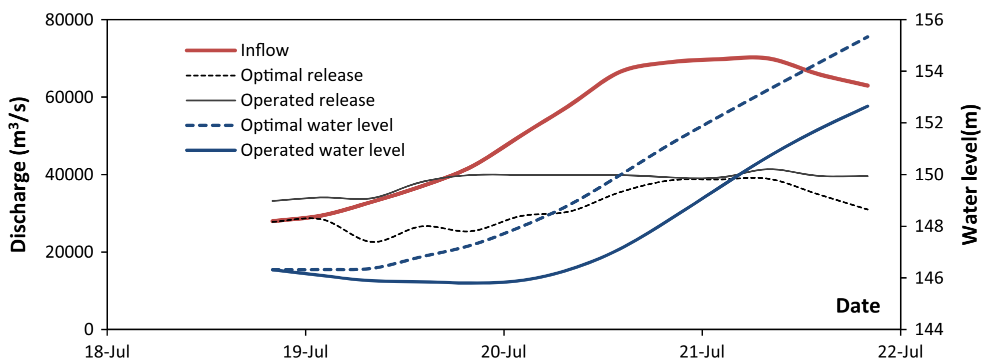


Fig. 7 Forecasted streamflow of the TGR in 2010

Fig. 8 Optimal reservoir operation in the 2010-7-20 8:00



$$F_2 = \min \max_{t=t_1,t_2,\ldots,t_n} R_t \quad \Leftrightarrow \quad F_2 = \min \sum_{t=t_1}^{t_n} R_t^2 \tag{17}$$

(3) Maximization of the hydropower generation:

$$F_3 = \max \sum_{t=t_1}^{t_n} N_t \tag{18}$$

where N_t denotes the hydropower generation during time period t. It is a function of release R_t (m^3/s) and water head H_t (m). Specifically, power output is calculated as $R_t = \min(KR_tH_t, N_{\max})$, where K is a constant coefficient (m/s^2, say 8.8 in the case study) that includes generating efficiencies and the specific weight of water, water head H_t is a function of the reservoir storage volume and the tail water level, and $N_{\max}$ is the maximum power output.

The constraints are Eqs. (1)–(3). The above optimization model has multiple objectives, which have been assigned variance weights to transform into a single objective problem. In this way, Pareto solutions have been produced.

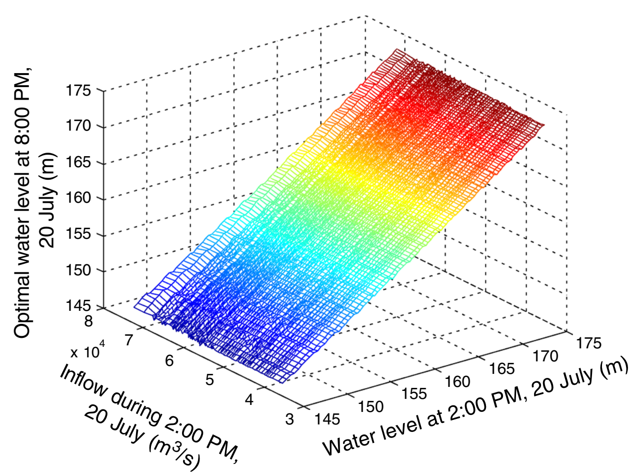


Fig. 9 Optimal operating policy in the 2010-7-20 8:00

The final decision is arbitrarily made by selecting a reasonable one. In this case study, the weights are set to 0.3, 0.3 and 0.4 for the Eqs. (16)–(18) respectively. With the SSDP method, Fig. 9 demonstrates the optimal operating

Table 1 The critical values based on the design flood hydrographs

Flood frequency (%)	Flood peak of inflow (m^3/s)	Maximum reservoir release (m^3/s)	Maximum reservoir water level (m)
0.01	111,800	100,200	175.0
0.1	97,800	67,900	173.7
1	82,900	53,900	161.9
5	71,300	53,900	153.1

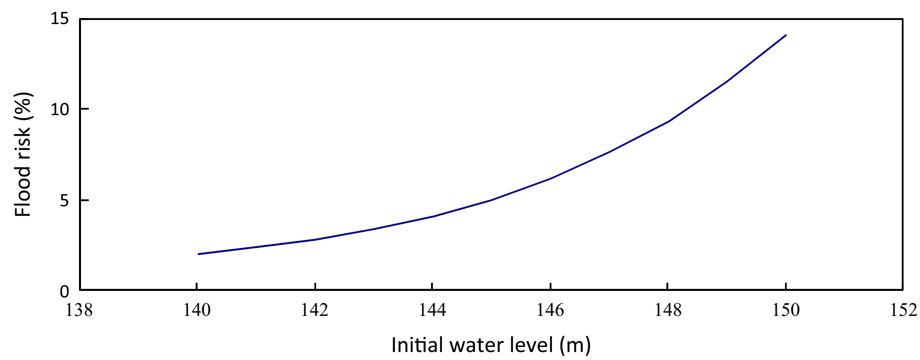


Fig. 10 Relationship between the reservoir initial water level and flood risk of upstream based on the critical value of 153.1 m (5 % design flood hydrograph)

policy for the 8:00 AM, July 20, 2010. As shown in Fig. 8, the optimal operation seems more aggressive and store more water for hydropower compared with historical operation.

3.4 Risk analysis

Table 1 defines four typical risks for the TGR based on the design flood hydrographs. The critical water level and release are listed, which is used to evaluate the reservoir real-time operation. Again, the risk in the unpredicted time is calculated based upon the design flood hydrographs and reservoir routing. For example, Fig. 10 shows the relationship between the initial water level and the risk for the critical value of 153.1 m (5 % design flood hydrograph).

3.4.1 Release control model

By fixed the reservoir releases to the operated or optimal one, the release control model is set up. In this case, the risk of downstream is equal to zero and only upstream risk need to evaluate. As shown in Table 2, the operated operation produce 1.44 billion kWh hydropower with a flood risk of 2.39 % for the upstream, which is acceptable since the design flood risk is 5 % (20-year return period). On the other hand, the optimal operation has a flood risk of 4.95 % and produces 1.58 billion kWh hydropower. Additionally, the end water level is higher than the operated one, which means more energy to produce under the conditions that risks are controlled within acceptable value (5 %).

3.4.2 Water level control model

Similarly, the reservoir water levels are kept fixed and the corresponding reservoir releases scenarios are used for risk analysis. Again, Table 2 shows that the operated operation produce 1.44 billion kWh hydropower with a flood risk of 3.65 % for the downstream, while the optimal operation has a flood risk of 5.00 % and produces 1.60 billion kWh hydropower, which means that the optimal one has an acceptable risk and produces more energy.

Table 2 Risks and profits of four operation schemes for the 2010 floods

Schemes		Reservoir risk (%)		Hydropower generation (billion kWh)	End water level (m)
		Downstream	Upstream		
Operated scheme	Release control	–	2.39	1.44	152.41
	Water level control	3.46	–		
Optimized scheme	Release control	–	4.95	1.58	155.14
	Water level control	5.00	–	1.60	155.23

4 Conclusions

In this study, the reservoir real-time operating risk with ensemble-based hydrologic forecasting inputs is studied. With a case study of the Three Gorges Reservoir (TGR) for the 2010 flood, following conclusion could be drawn:

(1) A novel risk not only considering the risk within forecast lead-time but also in the unpredicted time is developed.
(2) The hydrologic forecasting is very important to the reservoir operation, and the proposed model provides a risk estimated method, which units with yearly scale, associates with the flood protection standards (described with return periods) that can be used as the acceptable level to operate reservoir.

Although a framework for the ensemble-based forecasts has been set up, a number of issues need to further research, such as how to trade-offs between risks and profits, and the selection of the acceptable risk based upon economic analysis.

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