Evaluation of the effective forecast and decision horizon in optimal hydropower generation considering medium-range precipitation forecasts

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ABSTRACT

This paper presents a rolling horizon control (RHC) model to evaluate the effective forecast horizon (EFH) of 10-day forecast inflows derived from quantitative precipitation forecasts (QPFs) and the effective decision horizon (EDH) for hydropower generation. This paper takes the Huanren hydropower reservoir located in the northeast of China as a case study. Firstly, the 10-day forecast inflows are derived from the QPFs. Then the hydropower generation processes are simulated by the RHC model, and the performances of hydropower generation with different EFHs and EDHs are evaluated, respectively. The results show that: (1) the RHC can adapt to varying conditions by re-optimizing the decisions during the EFH; (2) with the EFH increasing, the hydroelectric reliability increases and the efficiency decreases, while the efficiency and reliability are improved with shortened the EDH.

Key words | effective decision horizon, effective forecast horizon, hydropower generation, quantitative precipitation forecasts, rolling horizon control

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INTRODUCTION

With the development of weather forecasting technology, quantitative precipitation forecasts (QPFs) have become more and more popular for optimal reservoir operations (Ngo *et al.* 2007; Wang *et al.* 2012; Xu *et al.* 2014; Zhang *et al.* 2018). With forecast horizons extending, medium-range QPFs have gained increasing attention for how they may be used to improve reservoir operations (Xu *et al.* 2013, 2014). Although the accuracy and reliability of medium-range QPFs are inferior to those of short-range QPFs, they have proven to be useful for reservoir operations (Bravo *et al.* 2009; Tang *et al.* 2010; Herr & Krzysztofowicz 2015; Wu *et al.* 2017).

In reservoir operations, the primary limitation of the forecast inflows is high uncertainty, which mainly comes from the uncertainty of QPFs (Mascaro *et al.* 2010; Xu *et al.* 2014; Qi *et al.* 2016; Ran *et al.* 2018). Recent studies have demonstrated that the uncertainty of the QPFs or inflow forecasts generally increase with the forecast horizon extending (Zhao *et al.* 2012; Peng *et al.* 2016). For multi-period problems, such as reservoir operation problems, longer forecast horizons can provide more information for decision-making to avoid myopic solutions (Huang & Ahmed 2010). With the forecast horizon extending, the forecasting of information with a longer forecast horizon affects initial decisions (Peng *et al.* 2016). Thus, it is necessary to do further research on the influence of the uncertainty before applying QPFs and forecasting inflows to make decisions. Based on the analysis above, there are three fundamental problems to be solved in this study: (1) how long should the forecast horizon be for the forecast inflow to be useful for hydropower generation with high efficiency and reliability, when the forecast horizon is defined as the effective forecast horizon (EFH); (2) how long should decisions be executed with high efficiency

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and reliability by using the forecast inflows, when the length of the decisions is defined as the effective decision horizon (EDH); (3) based on the results of the EFH and EDH, considering forecast inflow uncertainty reasonably to improve forecast inflow utilization.

Instead of the conventional fixed-length forecast horizon and decision horizon, there is a significant advantage to using dynamic rolling horizons to re-optimize the operational decisions dynamically according to updated information (Bardhan *et al.* 2013; Wang *et al.* 2014; Zulkafli & Kopanos 2018). The rolling horizon control (RHC) model based on the forecasting model and optimization model has a strong ability to adapt to varying conditions. Richalet *et al.* (1978) indicated that the decision-making behavior of the RHC is analogous to that of humans in varying conditions. This model decomposes the optimal problem of an entire planning horizon into several subproblems to reduce the computational burden and adapt to the varying conditions (Zhou *et al.* 2017). Thus, the RHC is a powerful method to solve dynamic stochastic problems. The framework provides a method to investigate the stability of the operational decisions and the influence of the forecasting uncertainty (Bardhan *et al.* 2013; Zhou *et al.* 2017; Bertazzi & Maggioni 2018).

The primary purpose of this paper is to investigate the EFH of the forecast inflows derived from medium-range QPFs and the EDH for hydropower operation. In this study, an RHC model is developed to evaluate the performances of hydropower operations, which are affected by the uncertainties of forecast inflows. Based on the RHC model, performances with different forecast horizons and decision horizons are evaluated, respectively. This study takes China's Huanren hydropower reservoir as a case study, and the real-time QPFs published by the Global Forecast System (QPFs-GFS) are utilized to forecast the inflows. Then the performances with different EFHs and EDHs are quantified and compared based on the forecast inflows.

ROLLING HORIZON CONTROL

The RHC model is constituted by combining the inflow forecasting model and the hydropower operation optimization model. The inflow forecasting model is used to forecast the inflows during the forecast horizon, and the operational policies are derived by the optimization model. The RHC model is introduced below.

Inflow forecasting model

In the case study, the multiple linear regression model and the Xinanjiang model are applied to simulate the inflows during the dry season and the wet season, respectively. The multiple linear regression model is built based on previous studies, and the parameters are determined using the least squares technique (Tang *et al.* 2010; Xu *et al.* 2014). The Xinanjiang model is a conceptual rainfall–runoff model and has been widely used in China, particularly in humid and semi-humid regions.

Hydropower optimal operation model

Decision strategy

In this study, the maximum forecast horizon is 10 days and the interval of the time step is 1 day. According to the forecasting of inflows, the operational decisions in the forecast horizon including n time steps defined as the EFH are optimized. The initial few time steps (λ) are defined as the EDH, and only the decisions from EDH with high efficiency and stability are implemented. The operation strategy is illustrated as below.

(a) Before re-optimization

When the operation is at time step t, the operational decisions of the entire planning horizon (denoted by $D_{\text{org}}(t)$) are represented as below:

$$D_{\text{org}}(t) = D_{\text{org}}(S(t)) + D_{\text{org}}(FH(t)) + D_{\text{org}}(Y(t)) \quad (1)$$

where t represents the indicator of the time step (day). $S(t)$, $FH(t)$ and $Y(t)$ represent the time steps during the executed horizon, the EFH, and the remaining horizon, respectively. $D_{\text{org}}(S(t))$, $D_{\text{org}}(FH(t))$ and $D_{\text{org}}(Y(t))$ represent the original decisions during $S(t)$, $FH(t)$ and $Y(t)$ respectively.

(b) Re-optimization and decision execution

The original decisions during the EFH at time step t are re-optimized. The optimal decisions (denoted by

$D_{org}(FH(t)))$ are obtained, and the optimal decisions during the EDH $(Fa(t))$ denoted by $D_{opt}(Fa(t))$ are executed. The optimal decisions during the EFH and the entire planning horizon are represented as below:

$$D_{opt}(FH(t)) = D_{opt}(Fa(t)) + D_{opt}(Fl(t)) \tag{2}$$

$$D_{opt}(t) = D_{opt}(S(t)) + D_{opt}(FH(t)) + D_{opt}(Y(t)) \tag{3}$$

where λ time-step decisions $(1 \le \lambda \le n)$ in $Fa(t)$ are executed. Apart from $Fa(t)$, the rest of the time steps and decisions during the EFH are denoted by $Fl(t)$ and $D_{opt}(Fl(t))$, respectively; n and N represent the time steps of the EFH and entire planning horizon, respectively.

(c) Operation rolls from t to $t+\lambda$

When decisions in $Fa(t)$ have been executed, the time step $(t+\lambda)$ is the initial time step of the next re-optimization. The executed time steps have transferred to $S(t+\lambda)$, and λ time steps in the remaining time steps $Y(t)$ (denoted by $Yk(t)$) are taken to fill in $FH(t+\lambda)$. The relationship of the operation variation from t to $t+\lambda$ is represented below;

$$S(t+\lambda) = S(t) + Fa(t) \tag{4}$$

$$FH(t+\lambda) = Fl(t) + Yk(t) \tag{5}$$

$$Y(t+\lambda) = Y(t) + Yk(t) \tag{6}$$

The re-optimization decisions at time step t become the original operational decisions at time step $t+\lambda$:

$$D_{org}(t+\lambda) = D_{opt}(t) \tag{7}$$

Moreover, the decision relationships are represented below:

$$D_{org}(S(t+\lambda)) = D_{opt}(S(t)) + D_{opt}(Fa(t)) \tag{8}$$

$$D_{org}(FH(t+\lambda)) = D_{opt}(Fl(t)) + D_{opt}(Yk(t)) \tag{9}$$

$$D_{org}(Y(t+\lambda)) = D_{opt}(Y(t)) + D_{opt}(Yk(t)) \tag{10}$$

Objective function during EFH

The operational objectives in this study are to maximize the total power production and to minimize the deviation from the required output to guarantee the stability of the power supply. Thus, the objective function consists of two components: the power production and the penalty for deviation from requirements:

$$J(D(FH(t)), k_t, Q_t) = Max\left[\sum_{j=0}^{n-1} B(k_{t+j}, q_{t+j}, l_{t+j}) \cdot \Delta t\right]$$
$$Q_t = (q_t, q_{t+1}, q_{t+2}, \cdots q_{t+n-1}) \tag{11}$$

$$B(k_{t+j}, q_{t+j}, l_{t+j}) = b(k_{t+j}, q_{t+j}, l_{t+j}) - \alpha \cdot \{Max[e - b(k_{t+j}, q_{t+j}, l_{t+j}), 0]\}^{\beta} \tag{12}$$

where $J(D(FH(t)), k_t, Q_t)$ represents the performance of hydropower generation during the EFH by giving decisions – $D(FH(t))$ and state variables of k_t and Q_t; k_t represents the storage at the beginning of time step t, and Q_t represents the vector of the forecast inflows during the EFH at time step t; l_{t+j} represents the storage at the end of time step $t+j$; q_{t+j} represents the inflow at time step $t+j$. $B(\cdot)$ is a function of hydropower generation, in which the penalty is evaluated by comparing the power generation $b(\cdot)$ (MW) and the system firm output of e (33 MW); α and β are penalty factors; Δt is the time step interval (hour).

Recursive equation of the RHC model

The performance of the hydropower reservoir operations depends on the storages and inflows in future time steps. The hydropower generation benefit in future time steps can be represented as expectations by using stochastic dynamic programming (SDP) (Tang *et al.* 2010; Xu *et al.* 2014; Zhang *et al.* 2018). The recursive equation is defined as:

$$f_t(k_t) = \underset{l_t}{Max}\,\{\overset{E}{_{q_t}}[B(k_t, q_t, l_t) + f_{t+1}(l_t)]\} \tag{13}$$

In the RHC model, the operational decisions in the EFH are optimized by dynamic programming (DP). The benefit in the remaining horizons is represented by the expectation value. The re-optimization recursive equation of the RHC is defined as below:

$$Y_t(D_t^n/k_t, Q_t, n, \lambda) = \underset{r}{Max}\,[J(D_r(FH(t)), k_t, Q_t) + f_{t+n}(k_{t+n})]_{r \in R} \tag{14}$$

where $D_r(FH(t))$ represents the rth operation trajectory, derived by DP during the forecast horizons. R is the total number of operation trajectories, and $r = 1, \cdots, R$, and $f_{t+n}(k_{t+n})$ represents the performance expectations in the remaining horizons by giving the storage at the beginning of the time step $t+n$. D_t^n represents the selected optimal decisions, which are executed during the EDH.

CASE STUDY

Huanren hydropower reservoir

Huanren hydropower reservoir, located in northeast China as shown in Figure 1, is chosen as a study case. The reservoir is located between latitudes $40°40'N \sim 42°15'N$ and longitudes $124°43'E \sim 126°50'E$ with an approximate area of 10,400 km^2. The mean annual rainfall is about 860 mm, and about 70% to 80% of the precipitation occurs in the wet season. The main features of the Huanren hydropower reservoir are summarized in Table 1.

Datasets

The Global Forecast System (GFS) was developed by the US National Centers for Environmental Prediction. In this study, the 10-day QPFs-GFS data have been daily downloaded since 2001. The forecast precipitation information at 00 GMT is used to simulate the forecast inflows per day.

The observed precipitation and observed inflow data from 1968 to 2010 are provided by the Hun River cascade hydropower development authority.

RESULTS AND DISCUSSION

In this study, the forecast precipitations from 2001 to 2010 are applied to forecast the inflows. Then the performances of the hydropower generation are evaluated at different EFHs and EDHs by using the forecast inflows, respectively.

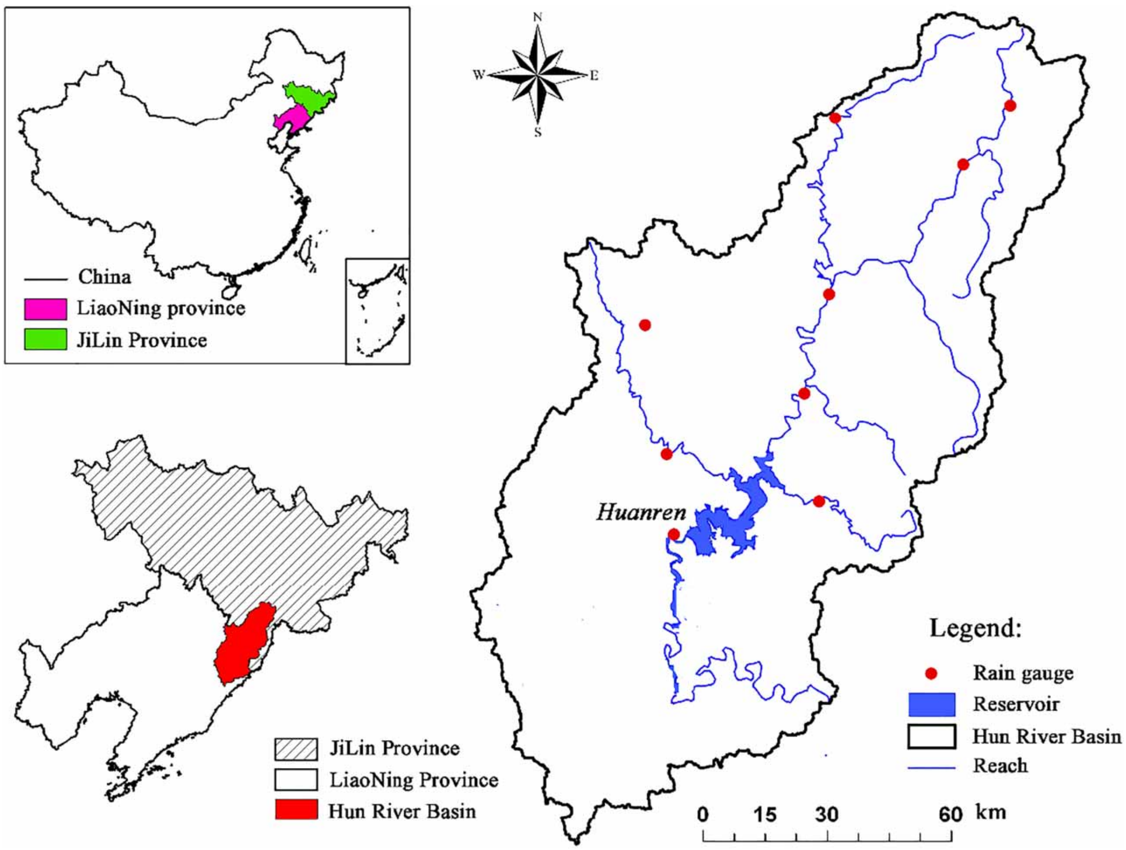

Figure 1 | The location of the Huanren hydropower reservoir in the Hun River Basin.

Table 1 | Basic parameters of the Huanren hydropower reservoir

Characteristic	Value	Characteristic	Value
Total storage (Mm^3)	3,460	Dead water level (m)	290
Usable storage (Mm^3)	2,199	Installed capacity (MW)	222
Dead storage (Mm^3)	1,380	Firm output (MW)	33
Normal water level (m)	300	Turbine capacity (m^3/s)	416

Analysis of QPFs-GFS

To evaluate the uncertainty of the QPFs-GFS in terms of different forecast horizons, the hydrological year is divided into four periods, as the dry season (from November to next April) and the wet season (May to June, July to August, and September to October). The empirical frequencies of the forecast uncertainty are obtained, respectively. And the quantiles of the forecast uncertainty, with frequencies as 10%, 30%, 50%, 80%, and 90%, are evaluated through the empirical frequencies, as shown in Figure 2. The precipitation forecast uncertainties from May to August in Figure 2(a) and 2(b) are more diffuse than those in the other periods and generally increase with the forecast horizon extending.

Analysis of inflow forecasts

In this study, the Nash–Sutcliffe Efficiency (NSE) and Root Mean Square Error (RMSE) are used to assess the accuracy of the average inflows with different forecast horizons. In the calibration and verification, the inflows are simulated by using the observed precipitation. Then, the medium-range QPFs from 2001 to 2010 are applied to forecast the inflows. The accuracy indicators during the calibration, verification, and forecasting periods are shown in Table 2.

During calibration and verification, the hydrological model performs well. The deviations are mainly from the forecast inflow process. With the forecast horizon extending, the deviations of the indicators are averaged. Thus, the values of NSE increase and the values of RMSE decrease with the forecast horizon extending.

During the forecasting periods, the values of the NSE decrease, and the values of the RMSE increase with the

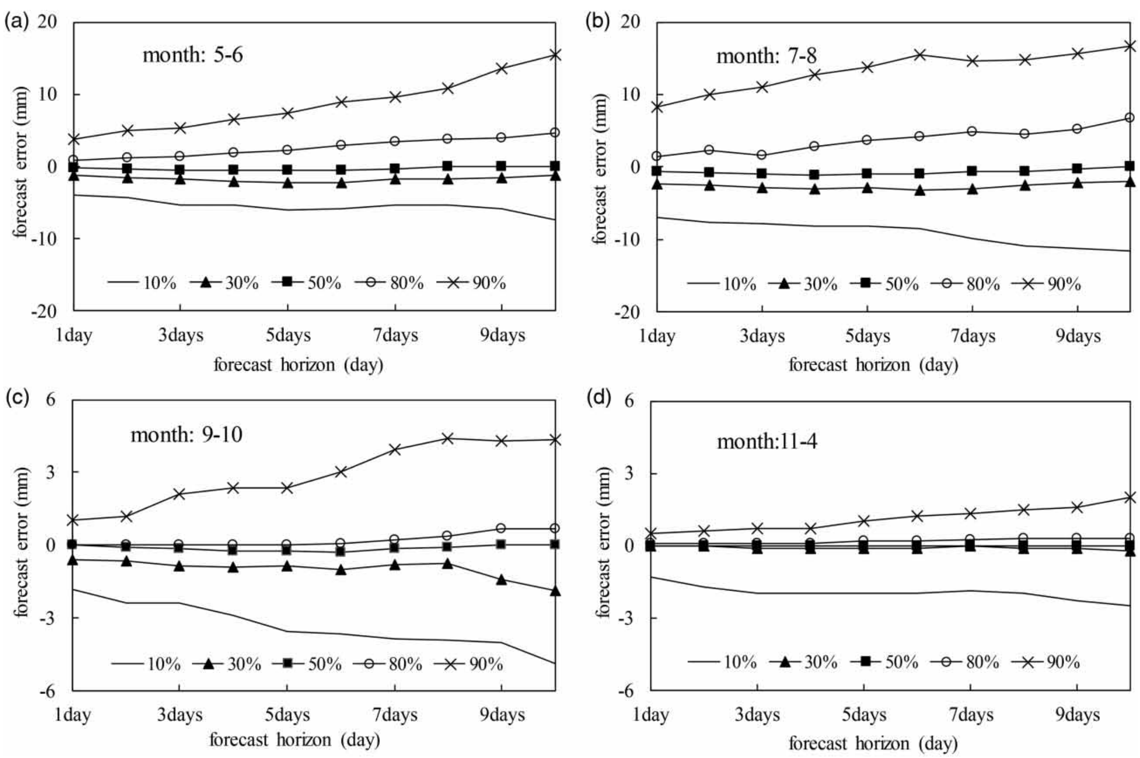

Figure 2 | The percentiles of precipitation forecast uncertainties vary as the forecast horizon extends.

Table 2 | The variation of the accuracy indicators in different periods with the forecast horizon extending

	NSE			RMSE (m^3/s)		
Forecast horizon (days)	**Calibration**	**Verification**	**Forecasting**	**Calibration**	**Verification**	**Forecasting**
1	0.87	0.86	0.80	34.32	42.05	46.42
2	0.87	0.86	0.81	33.65	42.05	46.17
3	0.88	0.86	0.81	33.25	41.35	45.10
4	0.88	0.86	0.80	33.16	41.15	45.63
5	0.89	0.88	0.78	31.49	39.25	47.68
6	0.92	0.88	0.76	30.87	37.11	49.84
7	0.94	0.91	0.75	28.62	34.39	50.08
8	0.93	0.91	0.74	28.36	35.14	51.52
9	0.94	0.91	0.74	28.36	34.27	51.83
10	0.94	0.92	0.73	27.21	32.40	54.82

forecast horizon extending. The result gives the conclusion that the accuracy of inflow forecasts is significantly affected by the forecast uncertainty of the QPFs (Bravo *et al.* 2009; Xu *et al.* 2014).

Performance evaluation

In the SDP model, the inflows are discretized into six intervals ($u = 6$), representing 15%, 30%, 45%, 60%, 75% and 90% percentiles. Moreover, the storage of the Huanren hydropower reservoir is discretized into 20 intervals. The penalty factors of α and β in the objective function are set to 1 and 2, respectively.

The forecast and observed inflows from 2001 to 2010 are used to evaluate the performances of the hydropower generation with different EFHs and EDHs. The annual hydropower generation (AHG) and reliability are chosen to evaluate the performances. The reliability is defined as the probability that the simulation output is not lower than the system firm output.

Varying effective decision horizons

Figure 3(a) and 3(b) show the performance indicators with the EDH varying from 1 day to 10 days. The indicators are evaluated by simulating the performances with the forecasts and observed inflows from 2001 to 2010, respectively, in which the EFH is fixed for 10 days.

Comparing the indicators of the AHG and reliability, the results indicate that hydropower generation performs effectively and stably by using the observed inflows. The observed inflows can be considered as accuracy information, which has low uncertainty. With the decision horizon extending, the performances can maintain stability.

However, forecast inflows are less reliable and have high uncertainty, and the optimal decisions are affected by the uncertainties in future time steps (Zhao *et al.* 2012; Zhou *et al.* 2017; Zulkafli & Kopanos 2018). In this study, the performances are diminished continually with the EDH extending. The results demonstrate that longer operations become unstable by using longer forecast inflows to make decisions. The optimal length of the EDH is approximately 4 days in this study case by using the 10-day forecast inflows from QPFs-GFS.

Varying effective forecast horizons

Figure 3(c) and 3(d) show the performance indicators of the EFH (n) vary from 1 day to 10 days, respectively. The EDH (λ) is fixed for 1 day to adapt the minimum EFH. The variations of the performance indicators are evaluated with different EFHs. The results show that the AHG and reliability increase constantly with EFH extending by using observed inflows.

Figure 3(c) shows that the AHG is diminished with the EFH extending by using the forecast inflows. The AHG is

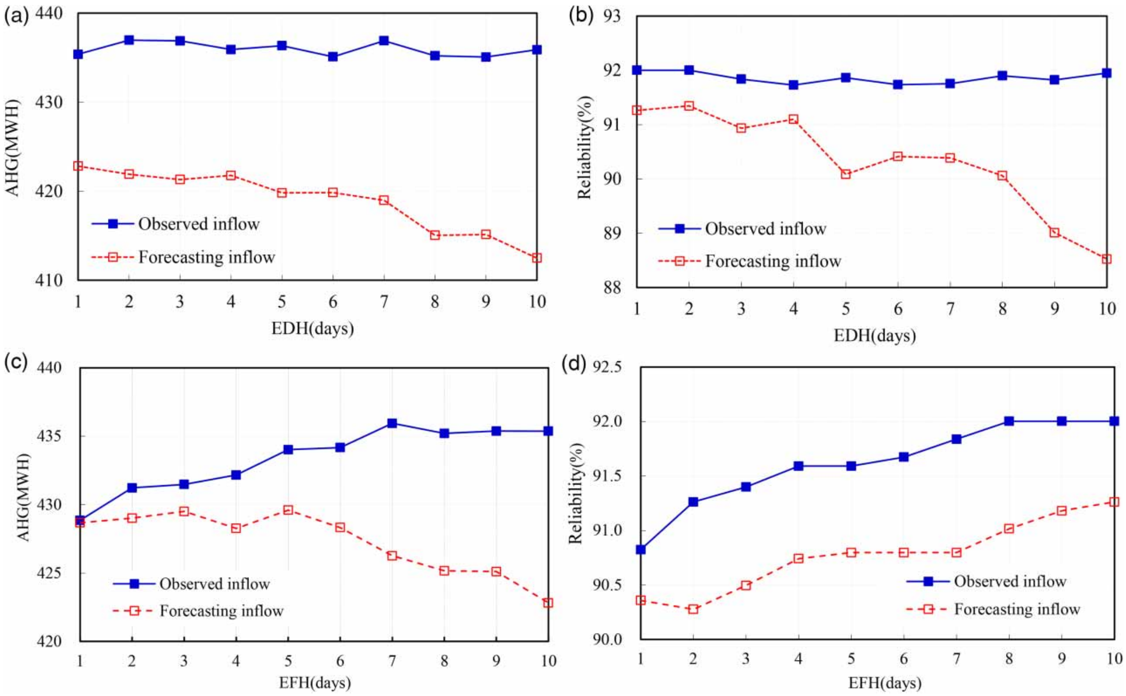

Figure 3 | The performance indicators vary as EDH and EFH extends.

mainly affected by operations during wet seasons, and the reliability is mainly affected by operations during dry seasons (Tang *et al.* 2010; Peng *et al.* 2016; Zhang *et al.* 2018). Figure 4(a) shows the water level processes during the wet season in wet years, i.e., 2006. When the forecast inflow is lower than the observed inflow, the release of hydropower generation during the EFH will be reduced. Then the reservoir will store more water and is prone to spill during the wet season, as shown in Figure 4(a). The spillages are irreversible AHG loss. That is the reason that the AHG is diminished with the EFH extending. Figure 4(b) shows water level processes in dry years, i.e., 2009. The reservoir stores more water for hydropower generation during the dry season, and the reliability improves with the EFH extending.

However, Figure 3(d) shows that the reliability increases with EFH extending by using forecast inflows. It demonstrates that the longer forecast inflows are still useful to hydropower generation. To improve the efficiency of the AHG, the forecast inflows in the first 4 days are assumed to be accurate in this case study and defined as the EDH, and the uncertainty in the remaining 6 days needs to be addressed by Bayesian theory (Xu *et al.* 2014; Zhang *et al.* 2018). The RHC model developed in this study adapts to the different decision and forecast horizon scenarios. Thus, in hydropower operation, the RHC can be applied to consider the EDH and EFH by using the forecast inflows.

CONCLUSIONS

This study investigates the effects of forecast inflow uncertainty on the performance of hydropower generation through varying the forecast and decision horizons. Comparing the performances with different forecast and decision horizons, the results obtained are summarized as below.

(1) In this study, the observed inflows are considered as accurate information. The operation performances demonstrate that when the forecast inflows have high accuracy, hydropower generation performs more efficiently and stably with the EFH extending.
(2) The efficiency and reliability of hydropower generation are diminished with the EDH extending by using forecast inflows. Shortening the EDH and the strategy of

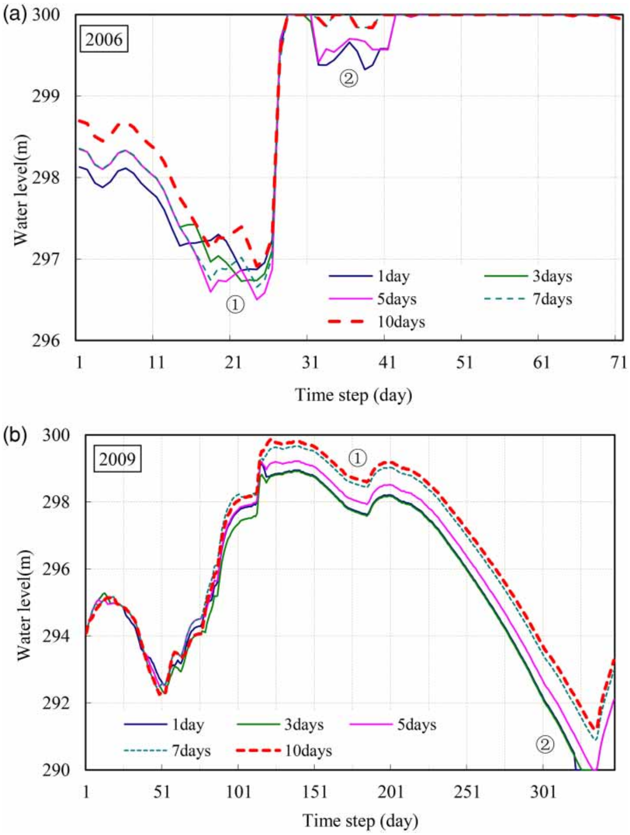

Figure 4 | The operation processes of the reservoir under different EFHs.

decision re-optimizing in the RHC model are beneficial for adapting the effect of the uncertainty of forecast inflows.

(3) The reliability increases with EFH extending by using observed and forecast inflows. It demonstrates that the longer forecast inflows are useful for hydropower generation. However, the uncertainty of the forecast inflows needs to be addressed to improve the efficiency of AHG.

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