

The application of ensemble precipitation forecasts to reservoir operation

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ABSTRACT

Although inflow forecasts are useful information that can be used for improving reservoir operation efficiency, uncertainty is still a challenge for getting sound operation results. Ensemble precipitation forecasts can take uncertainties under consideration, so they have been a research topic for improving reservoir operations. In this paper, a rainfall–runoff model, combined of a multiple linear regression model (for non-flood seasons) and the Xinanjiang model (for flood seasons), for inflow forecasts and a stochastic dynamic programming model for reservoir operations are developed in order to effectively use the ensemble precipitation forecast. To explore the best way for using the ensemble precipitation forecast, two post-processing techniques, i.e., ensemble forecast averaging (EFA) and interval value (IV), are tested. The ensemble precipitation forecast from the European Centre for Medium-Range Weather Forecasts (ECMWF) was chosen due to its high accuracy, and the Huanren reservoir, located in China, was used to test the newly developed models. The results show that, compared with the traditional rule curve, hydropower generation increases by 4.86% and 4.55%, respectively, when EFA and IV are used, which indicates that the use of ensemble forecasts facilitates considerable improvements in operating performance.

Key words | ensemble precipitation forecasts, inflow forecast, reservoir operation, stochastic dynamic programming model

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INTRODUCTION

With advances in weather forecasting and hydrologic modeling, inflow forecasts have been used increasingly in reservoir operations, and many studies have shown that inflow forecasts can improve reservoir operation efficiency (Peng *et al.* 2011; Zhao & Zhao 2014; Ahmed *et al.* 2015). However, applications of inflow forecasts to reservoir operation are constrained by their uncertainty. The main source of uncertainty, for inflow forecasts, is the uncertainty of precipitation (Zhao *et al.* 2012).

Precipitation forecasts are usually generated by numerical weather prediction (NWP) models, and their uncertainty mainly results from errors related to the initial condition values, model errors linked to the approximate simulation of atmospheric processes of the numerical

models and the intrinsic chaotic characteristics of the atmosphere. A deterministic weather forecast, which does not include these uncertainties, can only provide a single value per time step, which depends on the estimation of the initial atmospheric conditions (Ahmed *et al.* 2015), while ensemble weather forecasts can provide a couple of values per time step and the uncertainty can be taken well into account. Therefore, ensemble weather forecasts have been widely used in inflow forecasts since they were produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) and the National Center for Environmental Prediction (NCEP) of the US National Weather Service (NWS) in 1992, respectively. In a study of inflow forecasts, Roulin &

Vannitsem (2005) used ensemble precipitation forecasts from the ECMWF in the ensemble inflow prediction systems of two catchments in Belgium and the results show that the prediction system using the ensemble precipitation forecasts performs better than that based on historical precipitation inputs and can extend the lead time. Komma *et al.* (2007) conducted a 48-hour flood forecast in the Austria Kamp basin using ensemble forecast precipitation produced by the ECMWF, and how the ensemble distribution of precipitation forecasts propagates in the catchment system is studied. Bourdin & Stull (2013) employed M2M ensemble precipitation forecast information to make predictions of the reservoir inflow of the Canada Daisy Lake Reservoir, and the results show that improvements using ensembles can be better realized after removal of bias. All these studies illustrate that adopting ensemble precipitation forecast information in inflow forecasting can effectively elongate forecast lead-time and improve forecast precision.

The aim of this study is to integrate ensemble inflow predictions into reservoir operations to improve reservoir operation efficiency. First, a rainfall–runoff model combined of a multiple linear regression model (for non-flood seasons) and the Xinanjiang model (for flood seasons) was developed to translate the ensemble precipitation forecasts from the ECMWF into ensemble inflow forecasts. Then a stochastic dynamic programming (SDP) model was developed for reservoir operation using ensemble inflow forecasts. Additionally, a new method for combining ensemble inflow forecasts with the SDP model is presented. The Huanren reservoir, which is located in northeast China, is used to test the feasibility and validity of the proposed models and methods.

STUDY AREA AND DATA

Study area

The Huanren reservoir basin, located on the middle reach of the Hun River in China, was selected as the study area. The location and description of the basin is provided in the Supplementary Material (available with the online version of this paper).

Data

The datasets used in this study include observed daily inflow, observed daily precipitation, and ensemble precipitation forecasts.

Observed daily precipitation and inflow data were obtained from the Hydrological Administration of Liaoning Province. The data series spans from 1968 to 2012.

The ensemble precipitation forecast data used in this study consist of one control forecast (CF) and 50 perturbed forecasts from the ECMWF, which is archived in the Observing System Research and Predictability Experiment (THORPEX) Interactive Grand Global Ensemble (TIGGE). The CF is created through a data-assimilation procedure, and the perturbed forecasts are generated by perturbed initial conditions (Ye *et al.* 2014). All of these forecasts have a forecasting lead time of 1–15 days. These data can be downloaded freely from <http://apps.ecmwf.int/datasets/data/tigge/levtype=sfc/type=cf/>. The focus of the study is the operation policies of 5 days, so the ensemble precipitation forecasts with a lead-time of 1–5 days from 2007 to 2012 are adopted to obtain the inflow forecast. The forecast data were first interpolated to the ten rain gauges, and then area precipitation was obtained using the Thiessen polygon method. The evapotranspiration of the reservoir is calculated as 3% of the water capacity of the reservoir according to design specifications.

METHODS

Rainfall–runoff models

The study area has two distinct seasons: flood and non-flood. Inflows in these two seasons have their own characteristics: inflow in the non-flood season is usually low and stable, i. e., with no significant variations, while inflow in the flood seasons is high and unstable due to heavy rainfall. Therefore, as in the study of Xu *et al.* (2014) inflow in the study area is predicted using a combined rainfall–runoff model: a multiple linear regression model for non-flood seasons and the Xinanjiang model for flood seasons (Zhao 1992).

The precipitation of the previous period, the average inflow of the previous period, and the ensemble

precipitation forecast from ECMWF for the next period are selected as the inputs of the multiple linear regression model to forecast the average inflow of the next period in the forecast period. It should be noted that in the calibration and verification periods, the observed precipitation of the next period is used instead of the ensemble precipitation forecast from the ECMWF, due to the fact that there is no precipitation forecast for the two periods.

As a conceptual rainfall–runoff model, the Xinanjiang model, proposed by Zhao (1992), has been widely used in the humid area of China (Cheng et al. 2006; Yang et al. 2011). The inputs for the model are determined beforehand, including daily precipitation and soil moisture indices, and the output is daily inflow. The parameters of the Xinanjiang model are calibrated using a genetic algorithm (GA). For details refer to Cheng et al. (2006).

Reservoir operation model

Objective function

The aims of the reservoir operation model in this study are to maximize the total power generation and to obtain a reliability that is higher than 80% without violating the constraints. Power generation is the most important performance indicator of the hydropower system. The reliability is the ratio of the periods that the outputs are not lower than the firm capacity and all operation periods. Therefore, the objective functions can be shown as follows:

$$\begin{cases} f_{opt}^n(Z_t, H_t) = \text{Max} \left[\sum_{t=1}^T E[B(Z_t, H_t, Z_{t+1})] \right] \\ B(Z_t, H_t, Z_{t+1}) = \left[b(Z_t, H_t, Z_{t+1}) \right. \\ \left. - \alpha \{ \text{Max}(e - b(Z_t, H_t, Z_{t+1}), 0) \}^\beta \right] \cdot \Delta t \\ R \geq 80\% \end{cases} \quad (1)$$

where $f_{opt}^n(\cdot)$ is the expected power generation from the current period t to T ; t is the period index, $t = 1, 2, \dots, T$; n is the number of time periods between the current period t and the last period T . Z_t and Z_{t+1} are the water levels at the beginning and end of period t , respectively. H_t is the hydrologic state variable for period t . E means the expected value. $B(\cdot)$ is the immediate power generation at period t , $b(\cdot)$ is the

output at period t , and e is the firm output; α and β are penalty factors, which are used to punish the reservoir performance, i.e. let the value of $B(\cdot)$ decrease correspondingly, when the value of $b(\cdot)$ is less than the firm capacity. Δt (h) is the time for decision interval. R is the reliability.

Recursive equation

In the present study, an SDP model that uses the current period's inflow Q_t as a hydrologic state variable is developed to obtain the optimal release during the operation periods. In the operation model, the uncertainty of the inflow is illustrated by considering the serial correlation between two consecutive periods, and in real operations, the inflow forecast is used directly with the assumption that the inflow is forecast accurately. The recursive equation is shown below.

$$f_{opt}^n(Z_t, Q_t) = \text{Max} \left[B_t(Z_t, Q_t, Z_{t+1}) + \sum_k P_{jk}^{t+1} \cdot f_{opt}^{n-1}(Z_{t+1}, Q_{t+1}) \right] \quad (2)$$

where $f_{opt}^{n-1}(\cdot)$ is the expected power generation from the next period $t+1$ to T . Q_t is the observed inflow during period t . P_{jk}^{t+1} i.e., $P_{Q_{t+1}|Q_t}$, is the probability that the flow Q_{t+1} in time period $t+1$ belongs to the class interval k , given that the flow Q_t in time period t belongs to the class interval j .

Post-processing techniques

The ensemble inflow forecast obtained using the rainfall–runoff models and the ECMWF ensemble precipitation forecast data can provide a couple of forecast information for reservoir generation operation, which means that operators can get more information for making decisions. However, it is a challenge to apply ensemble forecasts for reservoir operations because the diversity of this information may be very large, especially during flood seasons, which makes it difficult to select reliable information. To effectively apply the ensemble inflow forecast, two post-processing techniques are tested in this paper, and the details are shown below.

Ensemble forecast averaging

Ensemble forecast averaging (EFA) is a simple and common method for processing ensemble forecasts (i.e., the ensemble precipitation forecast and the ensemble inflow forecast). Its aim is to provide a value for each time point, and it is obtained through the arithmetic mean of ensemble members at each point. Due to the advantage of reducing the forecast error variance for an initial sample of normal, random initial analyses, the ensemble forecast average has been repeatedly shown to give a more accurate forecast than a single realization of the forecast model (Cane et al. 2013). In the present paper, EFA is used for the ensemble inflow forecast obtained using the ensemble precipitation forecast, and it can be described using the following equation:

$$y = \frac{1}{M} \sum_{m=1}^M F_m, \quad m = 1, 2, \dots, M \quad (3)$$

where y is the average forecast inflow, F_m is the inflow forecast obtained using member m of the ensemble precipitation forecast, and $M = 50$.

Interval value

In the SDP model, inflow is classified into different intervals to take into account the uncertainty of the inflow forecast. To combine the ensemble inflow forecast with the SDP model effectively, a new post-processing technique, named interval value (IV), is proposed in the present paper. The details of the technique are shown below.

- (1) For period t , count the number of the 50 perturbed members that fall within each interval $N_{t,i}$. That is,

$$N_{t,i} = \sum_{m=1}^M n_{t,m} \quad (4)$$

where $n_{t,m} = 1$ if the inflow forecast of member m for period t is in the interval i , else $n_{t,m} = 0$

- (2) Find the interval that has the maximum $N_{t,i}$, and it is deemed that the observed inflow of period i will be in the interval with the highest possibility.
- (3) The IV is used to make decisions in the real-time reservoir operations.

RESULTS

This section is divided into three sub-sections: the first part illustrates the result of ensemble forecasts of inflow, the second part is the operation policies obtained using the operation model, and the third part is the results of reservoir operation.

Ensemble predictions of inflow

To obtain the ensemble predictions for inflow, the inflow forecast models are calibrated and validated first using the data series from 1968 to 2006 and from 2007 to 2012, respectively. Then the 1–5 days ensemble precipitation forecasts of ECMWF from 2007 to 2012 are used to provide ensemble inflow forecasts, which will be applied in the operation model. The panels in the first and second rows of Figure 1 show the simulated inflow versus the observed inflow into Huanren reservoir for the non-flood season (using the multiple linear regression model), flood season (using the Xinanjiang model) and the whole series (using the combination of the multiple linear regression model and the Xinanjiang model) during the calibration and verification periods. It can be seen that the combined rainfall–runoff model performs well in the calibration and verification periods, with the Nash–Sutcliffe efficiency coefficients (NSEs) of the whole series being 0.92 and 0.89, respectively. This illustrates that the combined model can achieve a satisfactory result and can be used in the forecast period. Moreover, the NSEs of the non-flood season are smaller than those of the flood season. The reason is that the multiple linear regression model for the non-flood season only uses the precipitation of the present period and the precipitation and inflow of the previous period as input factors, and the winter snow melt, an important factor that affects the inflow, is not considered due to the lack of data, therefore the inflow of the non-flood season cannot be forecast well. While in the flood season, the main factor that affects inflow is precipitation, which has been used in the Xinanjiang model, so the flood season has better NSEs.

After being calibrated and validated, the combined rainfall–runoff model is applied to forecast the inflow using the 1–5 days ensemble precipitation forecasts, including one control and 50 perturbed members. The NSEs of the 51 ensemble

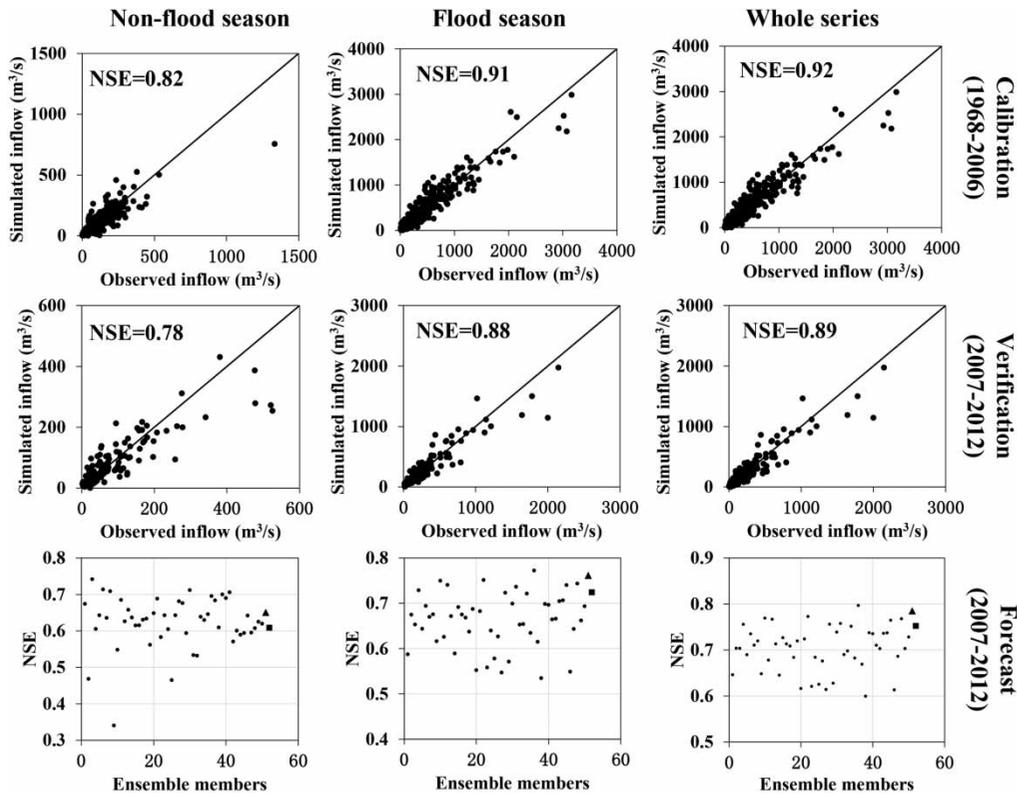


Figure 1 | Simulated results for the non-flood season, flood season and the whole series in the calibration, verification and forecast periods. In the panels of the third row, the dots, triangles and squares denote the results of perturbed members, average ensemble members and control members, respectively.

inflow forecasts are shown in the panels in the third row of Figure 1. In addition, the average of the ensemble inflow forecast, which was obtained using 50 perturbed members, is also shown in Figure 1, denoted as the squares. It can be seen that the NSEs in the forecast period are lower than those in the calibration and verification periods. This is because the precipitation used in the calibration and validation periods is the observed one, while that used in the forecast period is the ensemble precipitation forecasts, and the uncertainty of the precipitation forecasts results in a worse forecast performance. The NSEs of the non-flood season are more varied than those for the flood season and the whole series, with a range from 0.34 to 0.74. This illustrated that the performance of the multiple linear regression model for the non-flood season is more sensitive to the uncertainty of precipitation, because inflow in the non-flood season is usually lower than that of the flood season. The NSEs of the ensemble inflow forecast averaging are higher than those of the control inflow forecast in these three scenarios, which indicates that the EFA method can achieve a better result.

To further illustrate ensemble inflow forecasts, the results of the flood season during the forecast period from 2007 to 2012 are shown in Figure 2. It can be observed that the processes of the perturbed inflows, which are obtained using the 50 perturbed members of ECMWF, and the control inflow, which is obtained using the control member of ECMWF, show a similar tendency as the observed inflow. The processes of the perturbed inflows are crowded at low inflows but divergent at high inflows, which indicates that the perturbed inflows have small uncertainty at low inflows but higher uncertainty at high inflows. The range of the perturbed inflows covers the observed inflow well, given the probability that the observed inflows falling in the range are 72.2%, 77.8%, 72.2%, 75%, 80.6% and 77.8%. The EFA inflow and control inflows also show satisfactory results.

Operation policies

Operation policies from the operation model are derived using backward recursive equations by iterating until the

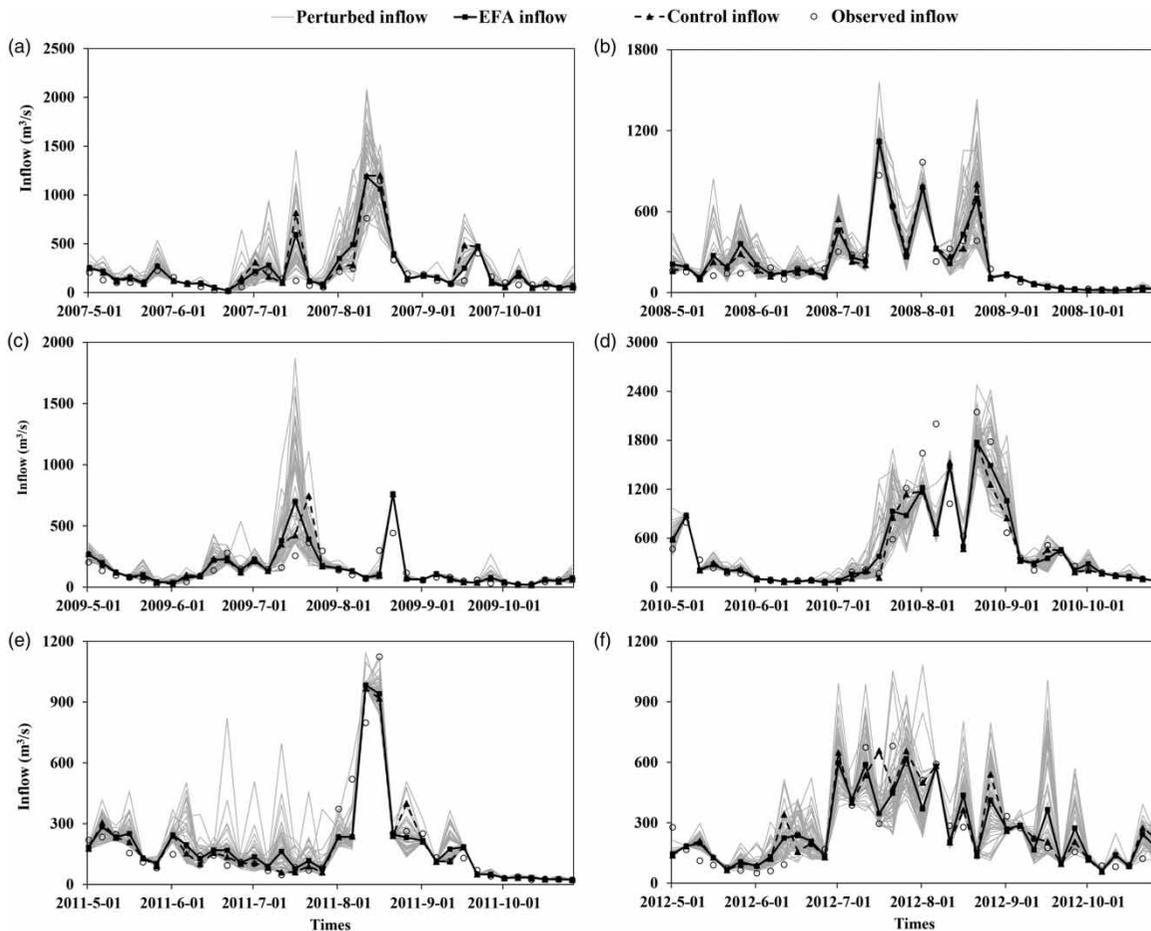


Figure 2 | The ensemble inflow forecasts for the flood season in the forecast period; (a)–(f) are for 2007–2012, respectively.

end storage reaches a steady state, with inflow data from 1968 to 2006. The penalty factors α and β in the objective function are set to 1 and 2, respectively, according to Tang et al. (2010). During the optimization processes, the inflow to the Huanren reservoir is discretized into six intervals, representing by 15%, 30%, 45%, 60%, 75%, and 90%, denoted as $i = 1, 2, \dots, 6$, respectively. The water level is discretized with an increment of 0.5 m.

The operation policies for every period will be obtained when the iteration stops. For example, the operation policies for 5 days from August 1 to 5 are presented in the Supplementary Material (available with the online version of this paper). It should be noted that the operation policies for every other period are similar to that for the 5 days from August 1 to 5, which are not shown in the present paper. Therefore, in the simulation process, the target water level of the specified period can be first obtained

from the operation policies, according to the inflow and the initial water level of this period, and then used to compute the output and hydropower generation.

Results of reservoir operation

In this study, the simulated inflows obtained using medium-range ensemble precipitation forecasts from ECMWF are applied in reservoir operation using three methods, i.e., SDP-CF, SDP-EFA and SDP-IV. And to effectively evaluate the efficiency of the three methods, the traditional rule curve (TRC) and SDP are also developed. The results are shown in Table S1 in the Supplementary Material (available online). It can be seen that compared with the result of TRC, all the SDPs perform better, with the hydropower generation being increased by 8.18%, 4.20%, 4.86% and 4.55%, respectively. The reason is that only the present water level is used

to make decisions in TRC, while in SDPs, the inflow forecast is used, which can provide more information to make better decisions. For the SDPs, the power generation obtained using the CF inflow, the EFA inflow and the IV inflow is less than that obtained using the observed inflow by 14.44×10^6 kW·h, 16.19×10^6 kW·h and 17.30×10^6 kW·h, respectively. This is because the former three forecast inflows are all obtained using the ensemble precipitation forecast and have many uncertainties, while the observed inflow can be deemed the perfect forecast inflow and has less uncertainty than other forecasted inflows.

Among SDP-CF, SDP-EFA, and SDP-IV, SDP-EFA performs best and SDP-CF performs worst. In the SDP-EFA and SDP-IV models, the post-processed results of the ensemble inflow forecast are used, which includes the merits of the ensemble forecasts, such as reducing the uncertainties caused by precipitation forecasts. Therefore, both of these

two models achieve higher hydropower generation than SDP-CF, in which only the forecast inflow obtained using the control member of the ensemble precipitation forecast is used. The hydropower generation of SDP-IV is slightly less than that of SDP-EFA. The reason is that for some periods, the members that achieve larger forecast inflows than the observed inflows are the dominants, which results in the members achieving accurate results being missed in the SDP-IV.

In order to further illustrate the reason that SDP-EFA performs better than SDP-IV, the operation processes for the period from August 2008 to January 2009 in the two models as well as the corresponding inflow forecasts are shown in Figure 3. From Figure 3(a), it can be seen that for the two periods August 16–20 and August 21–25, both the EFA inflow and the IV inflow are higher than the observed inflow, and the IV inflow shows a larger deviation.

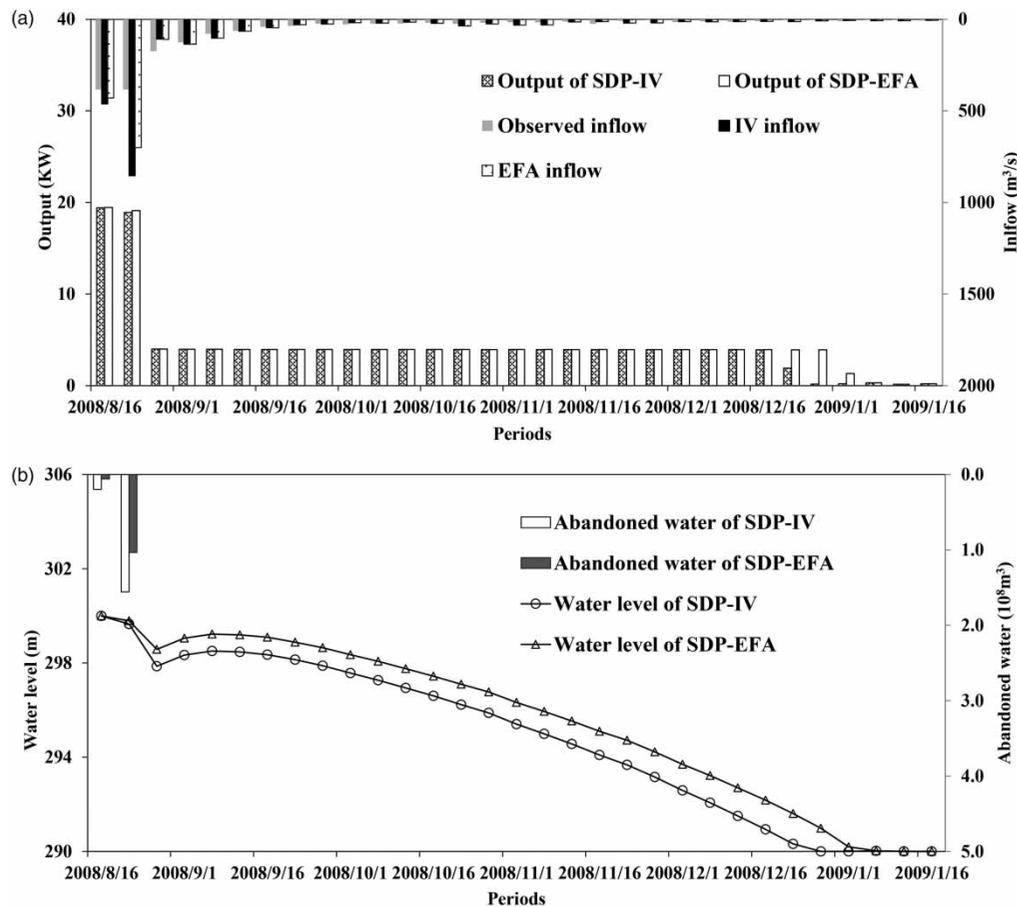


Figure 3 | The operation processes of the period from August 2008 to January 2009 in the SDP-EFA and SDP-IV models: (a) the output and inflow for every period, (b) the corresponding water level for every period.

When the decision for releasing is made during the period of August 16–20, SDP-IV produces more abandoned water than SDP-EFA, which leads to the target water levels of further periods in SDP-IV being lower than those in SDP-EFA, which can be observed in Figure 3(b), and the output of some periods, i.e., December 21–25, is less than ideal capacity. Therefore, SDP-IV produces less hydropower generation than SDP-EFA.

CONCLUSION

In this paper, the ensemble precipitation from ECMWF was first used as the input of the rainfall–runoff model to generate ensemble inflow forecasts, and the results illustrate that ensemble inflow forecasts show satisfactory performance and can be used for reservoir operation. Then, ensemble inflow forecasts are used as the input of the SDP model for reservoir operation through two methods, i.e., EFA and IV. The results show that both SDP-EFA and SDP-IV perform better than TRC, with the annual hydropower generation being increased by 4.86% and 4.55%, respectively, which indicates that ensemble precipitation forecasts can be used in real-time reservoir operations, thereby improving water-use efficiency and increasing the hydropower generation benefit of the reservoir.

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