Requirements and benefits of flow forecasting for improving hydropower generation

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ABSTRACT: This paper presents a methodology to identify the required lead time and accuracy of flow forecasting for improving hydropower generation of a reservoir, by simulating the benefits (in terms of electricity generated) obtained from the forecasting with varying lead times and accuracies. The benefit-lead time relationship was investigated only for perfect inflow forecasts, with a few selected forecasting lead times: 4, 10 days and 1 year. The water level and the release from the reservoir were then optimized. Based on the optimization results, the "threshold" lead time was identified, beyond which, further extension of the forecasting lead time will not benefit significantly. In order to investigate the benefit-accuracy relationship, the forecasting lead time was fixed to be 4 days, and the stochastic nature of the inflow was considered by means of generating noised synthesized inflow series for optimization. Noised inflow series were generated to mimic the flow forecasting with different levels of accuracy. These synthesized flow forecasting series served as input into the optimization model to simulate the benefits. The optimization model consists of two discretized deterministic dynamic programming (DDDP) models, one for long-term (monthly) and one for the short-term (daily) optimization. They were coupled together so that both short-term benefits (in a time horizon of flow forecasting lead time) and long-term benefits (in a time horizon of one year) were considered and balanced. The Qingjiang river in China and a reservoir on its main channel were taken as case study. The results revealed that the "threshold" lead time is about 30 days. A perfect inflow forecasting with 4 days lead time will realize 86% of the theoretical maximum electricity generated in one year. For inflow forecasting with a fixed lead time of 4 days and different forecasting accuracies, the benefits can increase by 3 to 11% (which is quite substantial) compared to the actual operation benefits. It is concluded that the definition of the appropriate lead time will depend mainly on the physical conditions of the basin and on the characteristics of the reservoir. The derived threshold lead time (about 30 days) is not feasible with the present flow forecasting techniques, but gives a theoretical upper limit for the extension of forecasting lead time. Criteria for the appropriate forecasting accuracy for a specific feasible lead-time should be defined from the benefit-accuracy relationship, starting from setting a preferred benefit level, in terms of percentage of the theoretical maximum. Inflow forecasting with a higher accuracy does not always increase the benefits, because these also depend on the operation strategies of the reservoir.

1 INTRODUCTION

A reservoir is a man-made body of water formed after a dam is built in a river. It is used for collecting and storing water, and is replenished by rain and (or) stream flow. In most cases, reservoirs are constructed and operated for multiple objectives: municipal water supplies, recreation, irrigation, hydropower generation, flood control, etc.. The basic function of reservoir operation is to satisfy these potentially conflicting objectives, and maximize the gross benefits that can arise from the operation. A reservoir can be conceptualized as a system with inflow as its input, the pool level (or storage) as its state, and the total release from the reservoir as the output. The total release can be divided and directed by hydraulic structures to different users to meet their corresponding operational objectives. In order to maximize the gross benefits, the pool level and release should be optimized in according with the amount of inflow to the reservoir for the corresponding time period. Therefore, a high quality inflow forecast is essential for applying the optimization. Although empirical operation functions drawn statistically from the historical records can be used, a real time optimization based on real time inflow forecasts is preferred for it increases the benefit and reduces the uncertainty by utilizing the most updated inflow information.

The quality of flow forecasting can be measured in terms of lead time and accuracy. The lead time of flow forecasting is the time interval between the issuing of the forecast and the occurrence of the forecasted flood event. The accuracy of flow forecasting is the difference between the amount forecasted and the value that actually occurs (Maidment, 1992). Because a balance has to be kept between the current benefits and the future benefits, inflow forecast with longer lead time enables an optimization for a longer time period. This leads to a better balance between immediate benefits and potential future benefits and therefore brings higher benefits in total. More accurate flow forecasting will reduce the possibility of mal-operation, therefore reduces potential damages and creates higher benefits. Therefore, an improved inflow forecasting with longer lead time and higher accuracy is always appreciated by reservoir operators. But one has to be aware that: (1) there is a limit for such improvement, there never exists an inflow forecasting with infinitely long lead time and 100% accuracy; (2) any extension of lead time and increasing of accuracy is costly. Therefore an evaluation of benefits arisen from the improved inflow forecasting is necessary to indicate whether it is worth the effort for the improvement, and to what extent it should be improved. In other words, if a flow forecasting model needs to be improved, it should be improved to an appropriate level.

Therefore the objective of this research is to find out the upper limit of the appropriate lead time and the appropriate accuracy with a certain lead time for flow forecasting. The resulting benefit-lead time-accuracy relationships will establish the foundation for determining the appropriate flow forecasting (appropriate lead time and accuracy) for reservoir operation.

A coupled discretized deterministic dynamic programming (DDDP) model is developed to simulate the benefits. The coupled DDDP model consists of both a long-term (monthly) and short-term (daily) optimization model using discretized deterministic dynamic programming as their optimization techniques. The stochastic nature of inflow is considered by means of generating noised synthesized inflow series for optimization.

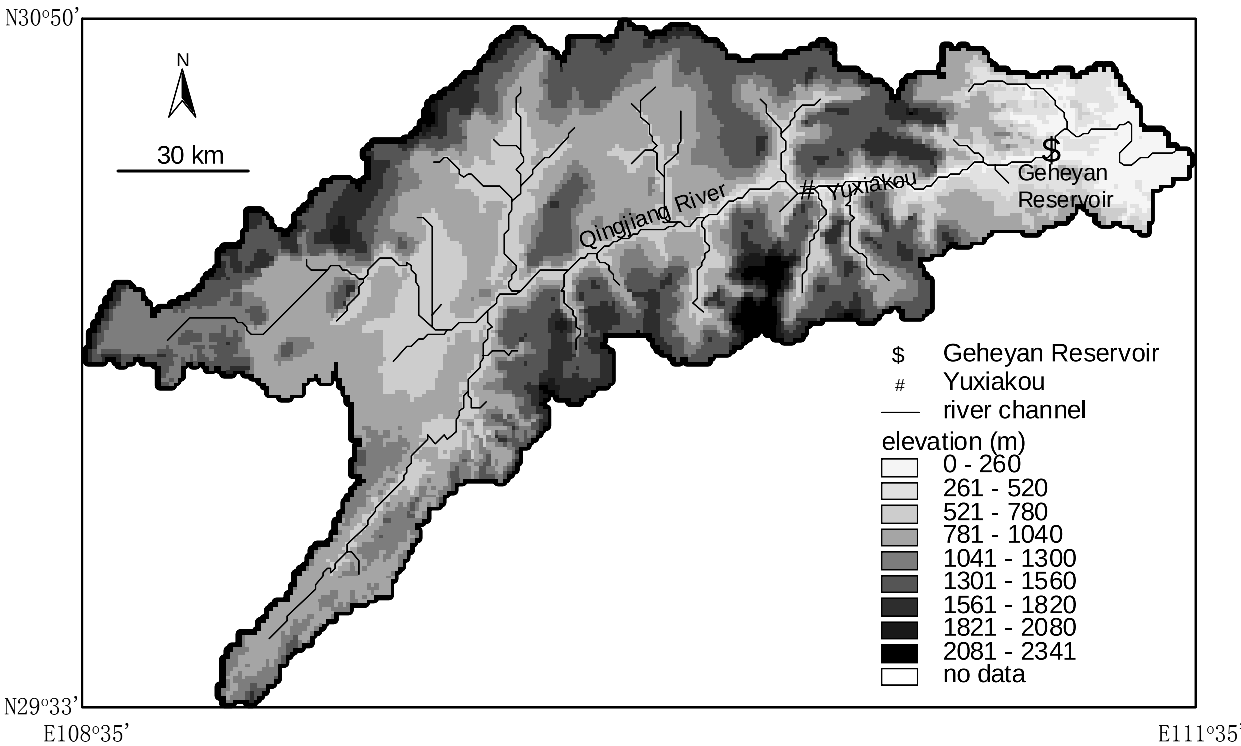

Figure 1. The geographic location of Qingjiang river basin and the Geheyan reservoir (the tail of the reservoir reaches Yuxiakou).

2 CASE STUDY AREA

The reservoir (Geheyan) used to apply the methodology proposed in the following section is located in one of the tributaries of the Changjiang River (Yangtze): the Qingjiang River. It is a comprehensive multipurpose water resources development project planned to utilize potential benefits of hydropower, flood defence, navigation, etc., with hydropower generation as its major interest. The reservoir started storing water from 10 April 1993. From 30 November 1994, all of the four generators started generating electricity. The geographic location of the Qingjiang river basin and the Geheyan reservoir is shown in Figure 1.

The main features of the catchment area upstream of the reservoir, the reservoir itself and the power plant are given in Table 1 (QHDC, 1998).

Table 1 Principal features of the Qingjiang catchment, Geheyan Reservoir and power plant.

	Characteristics	Unit	Value
Catchment	catchment area	km^2	14430
	average annual inflow volume	10^9 m^3	12.65
	average annual precipitation	mm	1400
	average annual discharge at the dam site	m^3/s	400
Reservoir	normal pool level (HN)	m	200
	dead water level (HD)	m	160
	total storage (ST)	10^9 m^3	3.431
	flood control storage (SFC)	10^9 m^3	0.72
	beneficial storage (SB)	10^9 m^3	1.975
	effective storage (SE)	10^9 m^3	2.286
	reservoir capacity factor*	%	15.6
Power plant	average head	m	108.9
	maximum head	m	121.4
	minimum head	m	80.7
	maximum discharge through one turbine	m^3/s	325
	number of power units		4
	total installed capacity	MW	1200
	firm output	MW	180
	average annual power output	kW.h	30.4

* Reservoir capacity factor= beneficial storage/average annual inflow.

The Qingjiang River is a mountainous river with steep mountains banking the stream. The depth of the valley ranges from 200 to 1000 meters, which created a canyon-type reservoir. The reservoir stretches for 90 km, although its surface area is only 55 km^2. Figure 2 shows the pool level-storage relationship. The relationship between the release to downstream and the tail water level is also important for calculating the generated electricity and is given in Figure 3.

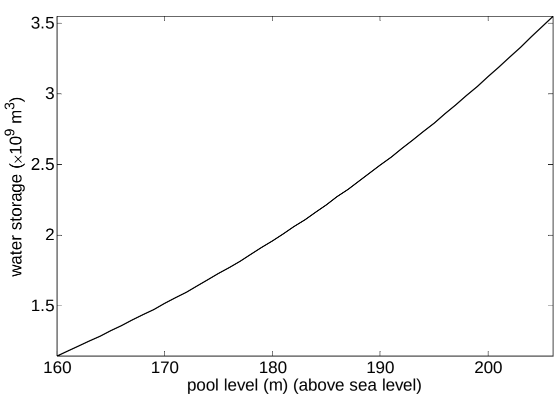

Figure 2. Storage-pool level relationship of Geheyan reservoir.

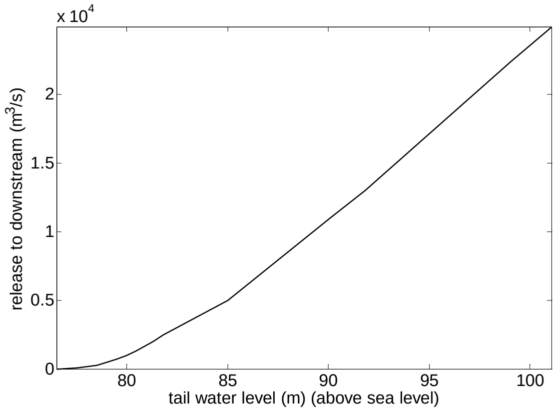

Figure 3. Release-tail water level relationship of Geheyan reservoir.

Rainfall in the Qingjiang river basin is very seasonal. Normally the rain season extends from May to October. Most big flooding events take place during this period. Therefore, the local water authority defined the first of May as the start of the hydrological year. For the most ideal operation, the water level of the reservoir will start decreasing from the beginning of the dry season (the first of November) to the dead water level (the minimum endurable water level of the reservoir under normal hydrological and operational conditions) before the first of May, and from then on, be refilled up to the normal pool level at the end of the flooding season.

3 METHODOLIGY

3.1 *A coupled short- and long-term dynamic model*

With inflow forecasting to a reservoir being available, extra benefit may be obtained by taking operation measures like: temporal over-storage and pre-releasing. Temporal over-storage is applicable in case the water level is already at normal pool level in non-flooding seasons or flood control level in flooding seasons. Pre-releasing can be applied in any seasons by using stored water to generate extra electricity and make space for impending flooding water. The realization of both measures needs first of all an appropriate forecasting of future inflows, and secondly an optimization technique to determine when to start the operation and how much to store or release. Traditional rule curve methods cannot take full advantage of the flow forecasting results. Therefore and due to the limitations arisen in the implementation of linear programming, dynamic programming will be used as the optimization technology in performing benefit analyses. The necessary balance between the long- and short-term benefits of reservoir operation necessitates the implementation of both long- and short-term optimization. That is, the operational decision should not only be made based on the short-term optimization results, but also based on the long-term optimization results. A time-decomposition method is used to couple these two models in a hierarchical structure.

Hydropower optimization is conducted by a trade-off evaluation of the benefits derived from releasing water in the current period and the benefits derived from storing the water for future use. The optimization of the current period has to be carried out under the guide of the long-term optimization results. A time-decomposition is necessary to transfer the long-term optimization results to short-term optimization operation. The relationship between long-term and short-term optimization has to be clarified. Therefore, a hierarchical optimization schedule is proposed which is similar to the one used by Karamouz et al. (2003). The structure of this method is shown in Figure 4, in which the optimization of hydropower reservoir operation consists of two steps: 1) long-term optimization on a monthly scale; 2) short-term optimization on a daily scale.

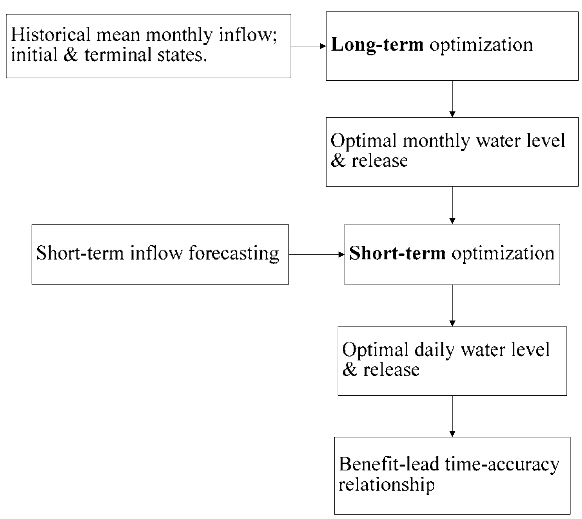

Figure 4. The hierarchical structure of long-term and short-term optimization of reservoir operation

The task of the long-term optimization is to optimize the average monthly release from the reservoir, and propose the optimal water level reached at the end of each month. In order to do this optimization, an estimation of the average monthly inflow to the reservoir is an important input to the model. There are a number of methods to do this long-lead inflow forecast, like the ones used by Burgers and Hoshi (1978) and Hamlet et al. (2002). These methods will not be used here, because our research focuses on the assessment of benefits from forecasting, not improving the forecasting method itself. The monthly average inflow series derived from the historical records will be used as the input for the optimization. According to the results obtained by Yeh et al. (1982), the use of historical averaged monthly inflow for reservoir optimization can already produce quite a lot of benefits (the hydropower output will be increased by 3.3% compared to the operation without considering the averaged monthly inflow).

The long-term optimization model will yield optimal monthly water levels and monthly mean releases. The proposed monthly water level will then be interpolated into daily water levels which will be the guidelines to the short-term optimization model.

The short-term optimization model will optimize the daily reservoir release based on short-term inflow forecasting, under the guide of the long-term optimization results. The resulting daily releases and water levels enable us to calculate the benefit obtained from short-term inflow forecasting with different levels of forecasting capabilities (lead-time and accuracy).

3.2 *The hierarchical structure for optimization of reservoir operation*

In order to figure out the relationship between the lead time and benefits, perfect inflow forecasts with a few representative lead times are input into the above-mentioned coupled DDDP model to simulate the benefits. The observed inflow data of one complete hydrological year will be used for these simulations. The hydrological year consists of a complete hydrological cycle: one dry season and one wet season, and also it covers a complete reservoir operation cycle: the pool level starts rising from the dead water level, ends at the dead water level after one year's operation. A threshold lead time is going to be identified after these simulations. The further extension of lead time beyond the threshold lead time will bring negligible benefits.

In order to investigate the relationship between inflow forecasting accuracies and the benefits a maximum feasible lead time is selected to demonstrate the methodology. Studying the benefit-accuracy relationship with lead times less than this maximal lead time can follow the same methodology. A lead time longer than this maximal lead time will not be feasible (or quite un-reliable) in reality and will therefore not be dealt with here. Noises are added to the observed inflow series with to mimic the forecasted series with errors (which will be noted as synthesized inflow series from now on). A new inflow generation model is used which is meant to keep three statistics (mean, standard deviation and lag-one auto-correlation coefficient of forecasting errors) stable compared to the observed inflow series. Different levels of inflow forecasting accuracy are assumed, and a number of synthesized inflow series are generated for each accuracy level. All synthesized inflow series serve as input into the coupled DDDP model to simulate the corresponding benefits to finally determine the benefits-accuracy relationship

The accuracy of the forecasting ranges from 40% of normalized deviation from the observed inflows (σ, definition is given below) to a perfect observation of the of the inflow series.

The forecasted series are modelled with noises superimposed on it to represent the error of the forecasting. The synthesization of forecasted inflow series considers the autocorrelation of the inflows (De Kok et al., 2004):

$$Q_t^{'} = Q_t + \beta_t \\ \beta_t = \delta_t \sigma Q_t + \alpha \beta_{t-1} \tag{1}$$

where $Q_t^{'}$ is the synthesized inflow at stage t; Q_t is the observed inflow at stage t; β_t is the noise added to the observed inflow series; δ_t is a scaling factor drawn from a random uniform distribution in the interval [-1, +1]; σ is an assumed absolute deviation from Q_t, and normalized with respect to Q_t, i.e., $\sigma = \left| Q_t^{'} - Q_t \right| / Q_t$; α is the autocorrelation coefficient of the difference $Q_t^{'} - Q_t$. $Q_t^{'} - Q_t$ measures the accuracy of the forecasting at time t. The presence of α introduces the fact that forecasting accuracy at a certain time is not completely random. It is partly related to the previous time step's forecasting accuracy. As a rule of thumb (De Kok et al., 2004), $\sigma + \alpha$ is less than 1. Compared to the method used by Yeh (1980, 1982), this inflow synthesization model considers the autocorrelation of the successive forecasting errors: $Q_t^{'} - Q_t$. Therefore, the resulting artificial inflow series are closer to the real situation.

An universal indicator for forecasting errors is used to measure the forecasting accuracies. The commonly used Nash-Sutcliffe coefficient (R2), originally proposed by Nash and Sutcliffe (1970), is adopted here. Once the forecasted series are synthesized by using equation (1), their R2 values are calculated. Next the synthesized forecasting series are used as input for the short-term and long-term optimization model to calculate the benefits.

For each optimization cycle, the initial state is the actual water level, and the terminal water level is the water level interpolated from the monthly optimization result. This implies that after the operation of one optimization cycle, if the inflow forecasting is perfect, the water level should be able to fall back to the water level proposed by the long-term optimization model. In this way, the results of the long-term optimization model form the basis and guidelines for the short-term optimization model, and compromises between the short-term benefit and the long-term benefit can be reached more economically.

4 RESULTS AND DISCUSSIONS

4.1 *Benefits obtained from flow forecasting with different lead times*

The 1997 hydrologic year is taken as an example time period to study the potential benefits (electricity) obtained from this year. The actual electricity generated during the hydrological year 1997 is 2.2×10^9 kW.h according to QHDC (1998). Three lead times, 4, 10 days and 1 year, are used to deduce the benefit-lead time relationship. In order to compare the benefits obtained from varying lead times (and in the following section, varying accuracies) of inflow forecasting, a benchmark benefit needs to be set for the comparison. Here, the benefits obtained from a perfect inflow forecast 1 year ahead is set as the benchmark benefit. It represents the theoretical maximum benefit which could be obtained from the forecasting and optimization. Besides the benchmark benefit, the optimization on power generation with 4 and 10 days ahead perfect inflow forecasts is also studied to deduce the effect of the lead time of inflow forecasting on power benefit. The results are presented in Figure 5. Figure 5(a) displayed the observed inflow series of Geheyan reservoir in the hydrological year1997. The optimized release, water level and power output trajectories are presented in Figure 5(b), (c) and (d). The optimal results for 1 year, 10 and 4 days perfect inflow forecasts are also calculated and included in the corresponding sub-figures. In Figure 5(c), the monthly water levels proposed by the long-term optimization model are also presented.

As shown in Figure 5(a), there is only one big flooding event in the flooding season of the hydrological year 1997. The maximum volume of flooding water for a duration of 72 hours is 2.32×10^9 m^3, corresponding to an annual probability of occurance of 4% according to QHDC (1998). There are 2 successive discharge peaks during this flooding event, with 2 days between their peaks.

Figure 5(b) displays the optimized releases from the reservoir. The releases (proposed by the optimization model) less than 1300 m^3/s (the maximum release via turbines) are released through turbines to generate electricity, whereas for releases higher than that, the redundant parts are released through flood-releasing works (spill gates, spillways or bypass conduits). The total wasted volume can be calculated by integrating the releases through flood-releasing works over time. The total wasted volumes under inflow forecasts with 1 year, 10 and 4 days' lead times are 0.8, 2.0 and 2.5×10^9 m^3 respectively, corresponding to 6, 16 and 20% of the average annual inflow volume (see Table 1)). Obviously, for inflow forecasts with a longer lead time, less water will be spilled. Before the arrival of the flooding event in July of 1997, inflow forecasts with longer lead times lead to earlier full-load operation of the generators, in order to generate more electricity and make more space for the impending water.

Also, this pre-releasing (before the arrival of the flood) operation can be identified easily from Figure 5(c). For inflow forecasts with longer lead times, the water level will start to decrease earlier before the arrival of the flood event as a result of optimization. Another factor revealed by Figure 5(c) is that although the flood event in July 1997 lasted for only 10 days, the reservoir needs to deplete the storage about 30 days before the beginning of the flood in order to generate maximum electricity. However, if the major operational purpose of the reservoir is different from power generation, like flood defence, the time to start pre-releasing the storage would be much later, because the releasing capacity of the flood sluices is much bigger than that of the turbines.

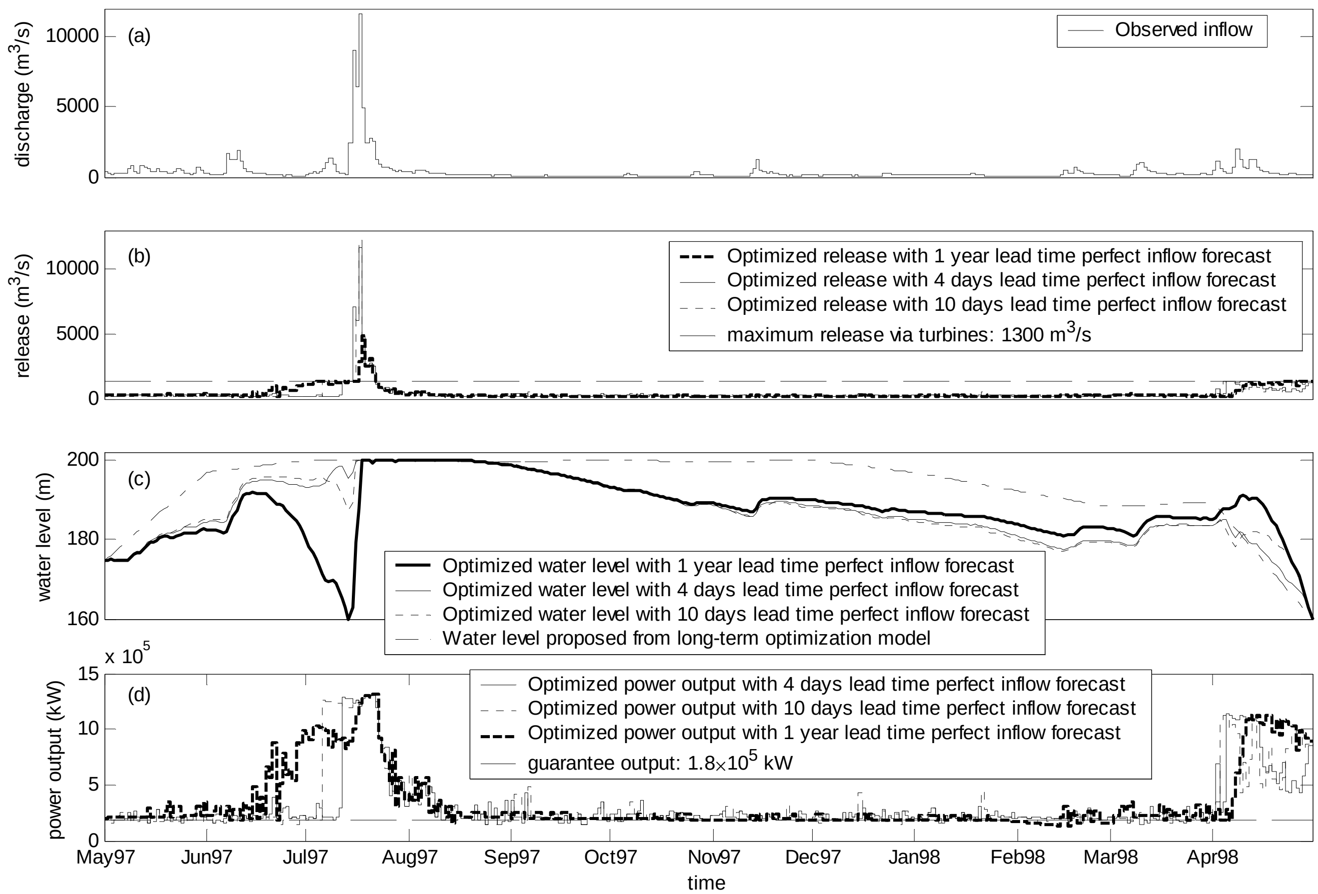

Figure 5. Optimized operation results under perfect inflow forecasts with lead time equalling 365, 10 and 4 days.
(a) The observed inflow series of Geheyan reservoir in the hydrological year1997;
(b) The optimized releases with 4, 10 days and 1 year perfect inflow forecasts;
(c) The optimized water levels with 4, 10 days and 1 year perfect inflow forecasts, and optimized water level from long-term optimization model;
(d) The optimized power output with 4, 10 days and 1 year perfect inflow forecasts;

Figure 5(d) shows the optimized power output in the hydrological year 1997. The corresponding total benefits (in terms of electricity generated) are listed in Table 2, where benefits obtained from the actual operation is displayed as well. As shown in Table 2, the benchmark benefits (3.0×10^9 kW.h) are 35% higher than the actually obtained benefits (2.2×10^9 kW.h). 10 and 4 days perfect inflow forecasts can respectively realize 93.5 and 85.7% of the benchmark benefit.

A threshold lead-time of about 30 days can be identified from Fig 5(c). Further extension of the forecasting lead-time beyond the threshold lead-time will not lead to much increase in benefit. No matter how feasible it is, the threshold lead-time gives the upper limit of an appropriate inflow forecasting in terms of lead-time. The value of a threshold lead-time depends on: (1) the physical feature of the reservoir: like the storage and releasing capacity of the turbines and the flood-releasing works; (2) the character of the impending flooding events: bigger flooding events (either bigger volume or higher peak discharge) will lead to longer threshold lead-times. As a lead-time of 30 days is absolutely infeasible in reality, the careful choice of an appropriate lead-time for a reservoir will therefore solely depend on the hydrological conditions of the river basin, (if rainfall forecasts are not considered), such as the hydrological response time of the basin. However, identifying the maximum feasible forecasting lead-time will not be dealt with in this benefit analysis research. In order to investigate the influence of the forecasting accuracies on the benefits, a feasible lead-time of 4 days will be chosen to simulate the benefits.

Table 2. Expected benefit under perfect inflow forecasting and actual benefit obtained from real operation.

	Lead time (days)	Benefit (10^9 kW.h)	Percent of benchmark
Perfect inflow	365	3.0	100
forecasts	10	2.8	93.5
	4	2.6	85.7
Actual operation	unclear	2.2	73.3

4.2 *Benefits obtained from flow forecasting with different accuracies*

Figure 6 and 7 present the optimized benefits calculated from the synthesized inflow series with different forecasting accuracies. As the actual total electricity generated from real operation is 2.2×10^9 kW.h, any 4-day ahead inflow forecasting with R2 greater than 0.70 (or RMAE less than 0.40) can at least realize 77% of the benchmark benefit (2.31×10^9 kW.h) as illustrated in Figure 6 and 7, an improvement of 3%. If we assume an R2 value of 0.90 (or an RMAE value of 0.25) of a 4-day ahead inflow forecasting to be feasible, then 80% of the benchmark benefit can be obtained, an increase of 6%. Thus, the benefits can vary from very small (3% increase compared to the real operation benefits) to quite substantial (11% increase compared to the real operation benefits).

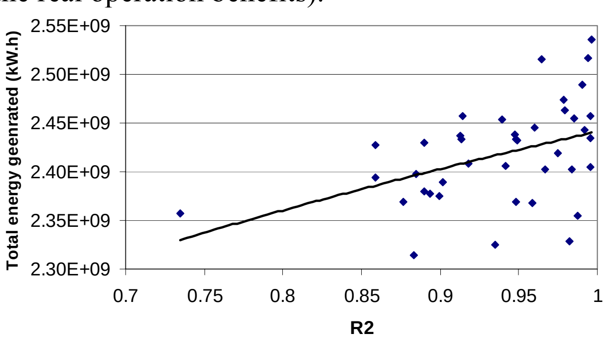

Figure 6. The relationship between benefits and the Nash-Suttcliffe coefficient of inflow forecasting series.

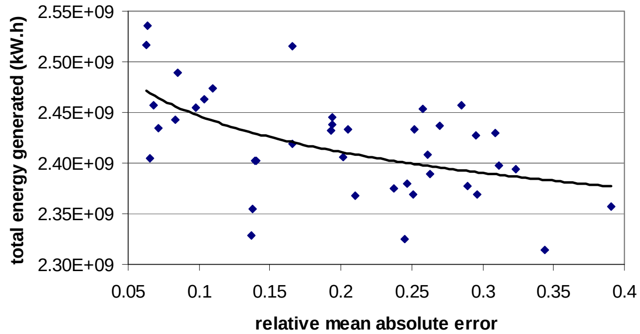

Figure 7. The relationship between the benefits and the relative mean absolute error.

It can also be seen from Figure 6 and 7 that high accuracy inflow forecasts do not always lead to high benefits. The relationships between benefit and forecasting accuracies are quite disperse. Figure 7 behaves slightly better, but the dots are still very much scattered. The following three reasons are meant to explain this dispersal of the relationships. (1) An un-optimal decision (because of the mis-estimation of the inflow) made at a certain stage will not only yield a local loss, but also contributes to future losses. For example, an overestimation of the inflow at the end of a flood season will lead to a decision to lower the water level. Because of a lack of inflow water during the following dry season, the low water level will be kept for a long period, which leads to a lower power output lasting for a long period. This effect will be less significant in the flooding season, because the mis-emptied volume can be easily filled up by abundant flooding water in flooding season. Because of the randomness in generating the forecasting errors for the synthesized inflow series, the chance of over-depletion of the storage and the long-term consequences of benefit losses are also random. Therefore, although the overall R2 values of inflow forecasts may be satisfactory, the variation of the benefits is still high. (2) Another reason for these dispersal benefit-forecasting accuracy relationships is that both R2 and RMAE are criteria designed for measuring the difference between the forecasted and observed inflow series (forecasting errors), not for measuring the increased electricity obtained from a better inflow forecasting. The forecasting errors do not take an explicit role in determining the amount of electricity generated. Its influence on the benefits takes effect through reservoir operation practices. Its influence will possibly either be depressed or exaggerated and is to some degree a random process as explained in the previous reason. A new, more effective measure of inflow forecasting accuracy for promoting power generation may be more appropriate for identifying this benefit-forecasting accuracy relationship. (3) For promoting power generation, inflow forecasting is not the only factor which has a fundamental influence on it. The operation strategies take another important role on the final output of electricity. The question of which one (forecasting or operation) takes a more important role still stays as a problem to be solved. As being aware that the inflow forecasting results are uncertain, the negative consequences arisen from it on power generation should be possibly alleviated by using appropriate operation strategies.

The criteria for an appropriately accurate inflow forecasting can be defined as a forecast that leads to a certain benefit which is expressed as a percentage of the benchmark, the theoretical maximal benefit. For example, if a benefit of 80% of the benchmark benefit (which is 2.40×10^9 kW.h) is required, an inflow forecasting with an accuracy in terms of an R2 value of 0.88 is necessary. The choice for the criteria depends not only on the reservoir operator's preferences, but also on the physical reality of the river basin studied. In general, large river basins with a long river channel and stable climate conditions can have relatively reliable inflow forecasting. Again, the feasibility of the required accuracy of the inflow forecasting is not the topic of this study.

5 CONCLUSION

A perfect inflow forecasting with 4 days lead time will realize 86% of the theoretical maximum electricity generated in one year. An increase of the lead time will increase the benefits. This benefit-increase will be quite insignificant for lead times greater than 30 days ("threshold" lead time).

The benefits obtained from actual operation turns out to be 74% of the theoretical maximum benefit. For inflow forecasting with a fixed lead time of 4 days and different forecasting accuracies, the benefits can range from 3 to 11% (which is quite substantial) with respect to the benefit obtained from the actual operations.

The definition of the appropriate lead time will depend mainly on the physical conditions of the basin and on the characteristics of the reservoir. The derived threshold lead time (30 days) is not feasible with the present flow forecasting techniques. Criteria for the appropriate forecasting accuracy for a specific feasible lead-time should be defined from the benefit-accuracy relationship, starting from setting a preferred benefit level in terms of percentage of the theoretical maximum. However, it has to be kept in mind that higher accuracy inflow forecasting does not always increase the benefits, although in general it does. The benefits obtained also depend on the operation strategies of the reservoir. The effect of the interaction between the inflow forecasting and the reservoir operation strategies on the benefits needs to be further explored.

REFERENCES

Burgers, S.J., Hoshi, K. 1978. Incorporation of forecasted seasonal runoff volumes into reservoir management. *Water Resources Series Technical Report No. 58.* 1978 November. Department of Civil and Environmental Engineering, University of Washington, Seattle, Washington, 98195.

De Kok, J.L., Van der Wal, K. and Booij, M.J. 2004. Appropriate accuracy of models for decision support systems: Case example for the Elbe River basin. In: C. Pahl, S. Schmidt and T. Jakeman (Eds.), *Complexity and Integrated Resources Management. Proc. Second Biennial Meeting of the International Environmental Modelling and Software Society*, 14-17 June 2004, Osnabrück, Germany.

Hamlet, A.F., Huppert, D. and Lettenmaier, D.P. 2002. Economic value of long-lead streamflow forecasts for Columbia river hydropower. *Journal of Water Resources Planning and Management*, 128(2): 91-101.

Karamouz, M., Szidarovszky, F. and Zahraie, B. 2003. *Water Resources Systems Analysis*, Lewis Publishers.

Maidment, D.R., 1992. Handbook of Hydrology. New York: McGraw-hill, Inc.

Nash, J. E. and Sutcliffe, J. V. 1970. River flow forecasting through conceptual models, Part 1-A discussion of principles. *Journal of Hydrology* 10: 282-290.

QHDC (Qingjiang Hydropower Development Cooperation-Reservoir Regulation Center), CWRC (Changjiang Water Resources Committee-Department of Planning) (Eds.), 1998. *Regulation rules of Geheyan reservoir-Qingjiang*, Hubei, China. (in Chinese).

Yeh, W.W.G., Becker, L., Cohn, M.J. and Zettlemoyer, R. 1980. *Benefits of long-range streamflow prediction*. Contribution No. 181, California Water Resources Center, University of California, 2102 Wickson Hall, Davis, CA 95616, USA.

Yeh, W.W-G., Becker, L. and Zettlemoyer, R. 1982. Worth of inflow forecast for reservoir operation, *Journal of Water Resources Planning and Management* 108: 257-269.