A real-time operation of the Three Gorges Reservoir with flood risk analysis
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ABSTRACT
Risk analysis is essential to reservoir operation. In this study, a new analysis for reservoir operation is proposed to enhance the utilization rate of the flood water from the Three Gorges Reservoir (TGR) during the flood season. Based on five scenarios of hydrology forecasting with the adaptive neuro-fuzzy inference system (ANFIS), a multi-objective optimum operation was implemented employing the risk control constraints of the genetic algorithm (GA) for the TGR. The results of this analysis indicated that the optimum hydropower generation was 5.7% higher than the usual operating hydropower generation, which suggested that, during flood season, it would be beneficial to increase hydropower generation from reservoirs, while maintaining a safe degree of flood risk.

Key words | ANFIS, flood risk, GA, multi-objective, reservoir optimal operation

INTRODUCTION
Building water reservoirs improves water supplies, hydroelectric energy, irrigation, navigation, and ecosystems, which are beneficial to the lives and livelihood of a nation's population. Administrators constantly search for the optimum methods and procedures for the reasonable use of water resources in operating reservoirs. However, because of the uncertainty of the stochastic water inflow, processing real-time reservoir operations is difficult. To control this uncertainty, quantitative risk analysis is considered to be an effective, widely applied method for real-time operation of a reservoir.

Many approaches have been proposed for analyzing flood risks. Thompson et al. (1997) discussed dam failure risks based on the efficiency of different evaluation methods, including, event trees, simple Monte Carlo sampling, Latin hypercube sampling, importance sampling and an analytical/stratified Monte Carlo method. Similarly, Kuo et al. (2007) assessed the overtopping risk of the Feitsui reservoir dam in Taiwan using Rosenblueth's point estimation method, Harr's point estimation method, Monte Carlo simulation, Latin hypercube sampling and the mean-value first-
order second-moment method. The authors found that the Monte Carlo method was very reliable for evaluation of the dam risk. Li et al. (2014) developed a procedure, which coupled a flood control risk module with utilization benefits analysis module, to derive an optimum refill rule. Linear regression was employed to quantitatively describe the possible linear trend of the inflow series. Zhou et al. (2015) developed a joint optimum refill operation model for cascade reservoirs to solve the conflict between the flood control and refill operation. The seasonal design inflow hydrographs for a given return period and historical daily inflow series were used in this model. Mediero et al. (2007) selected a probabilistic model that was based on Bayesian networks and calibrated with the results of a rainfall–runoff model coupled with a reservoir operation model. Huang & Hsieh (2010) proposed a new flood alert index. Their alert level was in response to potential flood severity and considered past inflow, present reservoir level and future reservoir outflow. Guo et al. (2014) proposed a methodology and procedure for flood disaster risk assessment in the central Liaoning Province. Vorogushyn et al. (2012) estimated the benefit of a proposed detention basin in the Middle Elbe and quantified the risk uncertainty by considering the uncertainty in inundation depth and duration. Chou & Wu (2015) established a decision support model for releasing reservoir storage prior to the arrival of a typhoon. This model predicted shortage risks associated with alternative pre-release scenarios providing reservoir operators a means to quantify the target pre-release strategy associated with a given level of acceptable shortage risk. McAnally & Williamson et al. (2014) provided rank-ordered lists of the highest risk zones, i.e., those with the greatest probability of failure combined with the most severe consequences, for several hundred protected areas in the Delta.

Two key points are found in the most of these prior studies. One is that the Monte Carlo method is a reliable method for risk analysis. The other is that the methods used for the inflow series description are too simple to sufficiently reflect the inflow process. However, it is often not possible to apply the Monte Carlo method to real reservoir operational risk analysis, because of the required heavy computational burden. Ensemble-based forecasts have the ability to describe the inflow uncertainty directly, because they easily depict the inflows of both the marginal distributions and their persistence via proposed scenarios. Therefore, the ensemble-based hydrologic forecasts (forecast scenarios) can be directly input into the reservoir operation model and used in the risk analysis. Based on this concept, in this study, risk analysis of reservoir real-time operation was performed using the ensemble-based hydrologic forecasts.

The objective of this study was to enhance the utilization rate of flood water without increasing the flood control risk for a multi-purpose reservoir during the flood season. Plate (2002) proposed that flood risk was the product of the event probability and its consequence. However, in this reported work, only event probability is considered. The risk indices, adopted from Liu et al. (2015) were used as a reference in this reported study. The risk indices were then added to the constraints of the reservoir operation, in place of the independent risk analysis, which simplified the flow of the reservoir operation.

In the following narrative, hydrologic simulation and reservoir simulation are detailed introduced in the Methodology section. A specific case and the scenarios of inflow forecasts are displayed in the Case study section. In the Results section, the results of inflow forecasts and optimal operation are presented and discussed. Finally, the Conclusions of this study are listed.

METHODOLOGY

As shown in Figure 1, the real-time reservoir operation together with the risk analysis was divided into two parts: the hydrologic simulation of reservoir inflow, simulated by the adaptive neuro-fuzzy inference system (ANFIS) and the reservoir simulation. Three objective functions were chosen for flood control and hydropower generation. Then, two flood risk indices were placed into the constraint conditions, with the exception of the common constraints such as the water balance equation, water storage capacity, and release constraint condition. Finally, a genetic algorithm (GA) was used to obtain the operation results.

Hydrologic simulation

An ANFIS is a multi-layer feed-forward network that uses neural network learning algorithms and fuzzy reasoning to map an input space to an output space. It can extract information and discover regularity from numerical data or
expert knowledge and then adaptively construct a rule base (Chen et al. 2006; Ahmed et al. 2007). The details are as follows (Chang & Chang 2006).

For simplicity, we assumed that the FIS under consideration has two inputs, x and y, and one output, z. For a first-order Sugeno fuzzy model, a typical rule set with two fuzzy if–then rules can be expressed as:

Rule 1: If \( x \) is \( A_1 \) and \( y \) is \( B_1 \) then \( z_1 = p_1 x_1 + q_1 x_2 + r_1 \) (1)

Rule 2: If \( x \) is \( A_2 \) and \( y \) is \( B_2 \) then \( z_2 = p_2 x_1 + q_2 x_2 + r_2 \) (2)

where \( p_i, q_i \) and \( r_i \) (\( i = 1 \) or \( 2 \)) are linear parameters in the then-part (consequent part) of the first-order Sugeno fuzzy model. The architecture of ANFIS consists of five layers (Figure 2) and a brief introduction of the model is as follows.

Layer 1: input nodes. Each node of this layer generates membership grades in which they belong to each of the appropriate fuzzy sets using membership functions.

\[
\begin{align*}
O_{1,i} &= \mu_{A_i}(x) \quad \text{for } i = 1, 2 \\
O_{1,i} &= \mu_{B_i-2}(y) \quad \text{for } i = 3, 4
\end{align*}
\]

Figure 1 | Flow chart of real-time reservoir operation.

Figure 2 | ANFIS architecture for two-input Sugeno fuzzy model with four rules (Chang & Chang 2006).
where $x, y$ are the crisp inputs to node $i$, and $A_i, B_i$ are the linguistic labels characterized by appropriate membership functions, $\mu_{A_i}, \mu_{B_i}$, respectively. Due to smoothness and concise notation, the Gaussian function has become increasingly popular for specifying fuzzy sets. So the Gaussian membership function was used in this study.

$$\mu_{A_i} = e^{-\frac{(x_i - c_i)^2}{2\sigma_i^2}}, \quad \mu_{B_i} = e^{-\frac{(y_i - c_i)^2}{2\sigma_i^2}}$$  \hspace{1cm} (4)

where $\{c_i, \sigma_i\}$ is the parameter set of the membership functions in the premise part of fuzzy if-then rules that changes the shapes of the membership function. $c_i$ is the mean and decide the center of the function, while $\sigma_i$ is the variance and decides the width of function curve.

Layer 2: rule nodes. In the second layer, the AND operator is applied to obtain one output that represents the result of the antecedent for that rule, i.e., firing strength. Firing strength means the degree to which the antecedent portion of a fuzzy rule is satisfied where it shapes the output function for the rule. Hence the outputs $O_{2,k}$ of this layer are the products of the corresponding degree from Layer 1.

$$O_{2,k} = w_k = \mu_{A_i}(x) \times \mu_{B_i}(y) \quad k = 1, \ldots, 4; i = 1, 2; j = 1, 2$$  \hspace{1cm} (5)

Layer 3: average nodes. In the third layer, the main objective is to calculate the ratio of each $i$th rule’s firing strength to the sum of all rules’ firing strength. Consequently, $w_i$ is taken as the normalized firing strength:

$$O_{3,i} = \frac{w_i}{\sum_{k=1}^{4} w_k} \quad k = 1, \ldots, 4$$  \hspace{1cm} (6)

Layer 4: consequent nodes. The node function of the fourth layer computes the contribution of each $i$th rule toward the total output and the function defined as:

$$O_{4,i} = \frac{w_i}{\sum_{i=1}^{4} w_i}(p_i x + q_i y + r_i), \quad i = 1, \ldots, 4$$  \hspace{1cm} (7)

where $\frac{w_i}{\sum_{i=1}^{4} w_i}$ is the $i$th node’s output from the previous layer. With respect to $\{p_i, q_i, r_i\}$, these parameters are the coefficients of this linear combination and are also the parameter set in the consequent part of the Sugeno fuzzy model.

Layer 5: output nodes. The single node computes the overall output by summing all of the incoming signals. Accordingly, the defuzzification process transforms each rule’s fuzzy results into a crisp output in this layer as defined by:

$$O_{5,1} = \sum_{i=1}^{4} \frac{w_i f_i}{\sum_{i=1}^{4} w_i}$$  \hspace{1cm} (8)

This network is trained by supervised learning. Our goal, therefore, is to train adaptive networks to enable them to approximate unknown functions provided by training data and then to find the precise value of the above parameters. The distinguishing characteristic of this approach is that ANFIS applies a hybrid-learning algorithm, termed the gradient descent method and the least-squares method, to update parameters. The gradient descent method is employed to tune premise non-linear parameters $(\{c_i, \sigma_i\})$, while the least-squares method is used to identify the consequent linear parameters $(\{p_i, q_i, r_i\})$.

Reservoir simulation

Objective function

1. The highest level of the optimization goal: the control of flooding

Minimization of the reservoir maximum water level, which can be described as:

$$\min \; \max (Z_{t_1}, Z_{t_2}, \ldots, Z_{t_n}) \quad t_i = t_1, \ldots, t_n$$  \hspace{1cm} (9)

Minimization of the reservoir maximum flood peak, which can be expressed as:

$$\min \; \max (O_{t_1}, O_{t_2}, \ldots, O_{t_n}) \quad t_i = t_1, \ldots, t_n$$  \hspace{1cm} (10)

2. The second level optimization goal: hydropower generation

Maximization of the hydropower generation:

$$\max \sum_{t_{i-1}=t_i}^{t_n} N_{t_i} \quad t_i = t_1, \ldots, t_n$$  \hspace{1cm} (11)

where $t_i$ is time $(t_1 = t_1, \ldots, t_n)$, $Z_{t_i} (m)$ is the water level of reservoir, $O_{t_i} (m^3/s)$ is release of reservoir. $N_{t_i}$ is the
hydropower generation, which is a function of release \( O_R \) (\( m^3/s \)) and water head \( H_R \) (m). The power output was calculated using the equation \( N_h = 9.81\eta O_R H_R \), where \( \eta \) is the efficiency of hydropower station and is equal to the product of hydraulic turbine efficiency, generator efficiency and sets of the rotation efficiency \( (\eta = (0.8-0.82)) \) in the Three Gorges Reservoir (TGR). In this study, 0.82 was used. The water head \( H_R \) is equal to the upstream water level minus the downstream water level.

The above optimization model has multiple objectives, which have been assigned different weights to transform it into a single objective problem. In this way, Pareto solutions were produced. The final decision was made by selecting a reasonable one and is formulated by the weighting method as follows:

\[
F = \min \sum_{i=1}^{t_n} (w_1 Z_i^2 + w_2 O_i^2 - w_3 N_i) \\text{(12)}
\]

The weighting coefficients were set to be \( w_1 = 0.4, w_2 = 0.4 \) and \( w_3 = 0.2 \). This implied that flood control was a higher priority than hydropower generation.

**Constraints**

(1) The common constraints employed

(i) The water balance equation:

\[
V_{i+1} = V_i + (I_i - O_i)\Delta t \quad t_i = t_1, \ldots, t_n \\text{(13)}
\]

(ii) Water storage capacity constraints:

\[
V_{\text{min}} < V < V_{\text{max}} \\text{(14)}
\]

(iii) Release constraints:

\[
O_{\text{min}} < O < O_{\text{max}} \\text{(15)}
\]

where \( I_i, O_i \) and \( V_i \) are denoted as reservoir inflow, \( t_i \) is the period of release or storage at time period \( t_i \), respectively and \( \Delta t \) is the time interval. The parameter \( O_{\text{min}} \) is the minimum reservoir release required for environmental considerations and navigation, \( O_{\text{max}} \) is the maximum reservoir release required for the downstream safety. The parameter \( V_{\text{min}} \) is the allowable minimum reservoir storage, which is often the storage corresponding to the dead water level. The parameter \( V_{\text{max}} \) is the storage capacity of reservoir, which is often the storage corresponding to the normal water level.

(2) The risk constraints

Generally, the frequency and severity of failure are considered in the risk analysis for a multi-purpose reservoir (Botzen et al. 2009; Lind et al. 2009). We, however, only discussed the probability of failure for the TGR. The risk can be estimated by an equation (Liu et al. 2015), which includes two flood risk indices. The details are as follows.

A scenario is defined here as a stream flow hydrograph. Based on the ensemble forecasts with \( m \) members, the risk is defined as the frequency of the failure of a number of members \( i, i/m \). Two flood risks, where either the release discharge or the reservoir water level is greater than a critical value, are considered to assess the risk of reservoir operation.

As shown in Figure 3, the future time period is divided into two stages by the forecast horizon point: the forecast lead-time (forecast horizon) and the unpredicted time. Based on the above two-stages, 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, while the other is risk in the unpredicted time. This is difficult to calculate due to floods after the lead-time, but it can be estimated using the reservoir routing with the design flood hydrographs. It is notable that the initial water level of the reservoir routing, i.e., the time of forecast horizon point, should begin with the reservoir end water level of stage one (reservoir routing with forecasts).

(a) Risk within forecast lead-time:

The release discharge or the reservoir water level, whichever 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.

\[
R_{L,\text{down}} = \text{Prob}(O > O_c) = \frac{\sum_{i=1}^{m} (O_i > O_c \forall t = t_1, t_2, \ldots, t_n)}{m} \\text{(16)}
\]
Assuming that the water level $Z_{i,n}$ at time $t_n$ is uncorrelated with the forthcoming flood, the risk can be estimated by:

$$R_{2,\text{down}} = \sum_{i=1}^{m} R_{\text{down}}(Z_i,t_n) P(Z_i,t_n) = \frac{\sum_{i=1}^{m} R_{\text{down}}(Z_i,t_n)}{m}$$  \hspace{1cm} (18)$$

where $Z_{i,n}$ is water level at time $t_n$ for scenario $i$. $P(Z_i,t_n)$ is the probability of end water level reach to $Z_{i,n}$ that is often set as equal probability, and $R_{\text{down}}(Z_i,t_n)$ is the frequency of any forthcoming flood when the storage level is $Z_{i,n}$, which 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 flow can be expressed as follows:

$$R_{2,\text{up}} = \sum_{i=1}^{m} R_{\text{up}}(Z_i,t_n) P(Z_i,t_n) = \frac{\sum_{i=1}^{m} R_{\text{up}}(Z_i,t_n)}{m}$$  \hspace{1cm} (19)$$

(c) Entire risk:
So the entire risks can be calculated as follows.

\( R_{\text{down}} = R_{1,\text{down}} + P(R_{2,\text{down}}) \frac{R_{1,\text{down}}}{m} \)

$$= \frac{\sum_{i=1}^{m} R_{\text{down}}(Z_i,t_n)}{m}$$  \hspace{1cm} (20)$$

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

Similarly, the entire risk of the upstream $R_{\text{up}}$ can be determined by:

$$R_{\text{up}} = \frac{\sum_{i=1}^{m} \{ Z_i | t > Z_c \} \forall t = t_1, t_2, \ldots t_n}{m} + \sum_{i=1}^{m} R_{\text{up}}(Z_i, t_n)$$  \hspace{1cm} (21)

Clearly, the proposed risk is on 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.

Four typical risks for the TGR based on the design flood hydrographs are displayed in Table 1. The risk constraints are:

$$R_{\text{down}} < 5\%$$  \hspace{1cm} (22)

$$R_{\text{up}} < 5\%$$  \hspace{1cm} (23)

**Optimization method**

To find the approach best suited to solve the problem of optimization, typical approaches were roughly classified into either traditional algorithms or intelligence algorithms and compared. Unlike traditional algorithms, intelligence algorithms have the advantage of an easy algorithm principle, good algorithm convergence and search speed, which tend to quickly lead to satisfying results. The GA, similar to Darwinian natural selection (Holland 1975; Goldberg 1987), has the capability of high-efficiency parallel computation, self-adaption, and random global search. GA starts with a population representing the possible solution set of the problem consisting of individuals selected through gene coding. After the initial population is generated, improved approximate solutions are evaluated by generational analysis according to the principle of survival of the fittest. Within each generation, individuals are selected based on high fitness to generate a new population through genetic operators of selection, crossover, and mutation. This process leads to resulting offspring that are better for acclimatization than their parents and the decoded elitists of the last generated population are regarded as the approximate optimum solutions, as shown in Figure 4 (Oliveira & Loucks 1997; Chang & Chen 1998).

In this study, seven reservoir storages, the input arguments from 10–16 June, 2010 were coded into chromosomes (simulation results) to initialize a random population. The fitness function was a combination of the objective function and constraint formulae from Equations (9) to (23). Roulette wheel parent selection was used to select the chromosomes for the offspring according to the fitness of the individual data. The probability of an individual proceeding to the next generation was equal to the ratio of its fitness to the sum of the individual fitness values over the whole population. The higher fitness

![Flow chart of GA](https://iwaponline.com/ws/article-pdf/16/2/551/412793/ws016020551.pdf)

**Table 1** The critical values based on the design flood hydrographs

<table>
<thead>
<tr>
<th>Flood frequency (%)</th>
<th>Flood peak of inflow (m$^3$/s)</th>
<th>Maximum reservoir release (m$^3$/s)</th>
<th>Maximum reservoir water level (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.01</td>
<td>111,800</td>
<td>100,200</td>
<td>175.0</td>
</tr>
<tr>
<td>0.1</td>
<td>97,800</td>
<td>67,900</td>
<td>173.7</td>
</tr>
<tr>
<td>1</td>
<td>82,900</td>
<td>53,900</td>
<td>161.9</td>
</tr>
<tr>
<td>5</td>
<td>71,300</td>
<td>53,900</td>
<td>153.1</td>
</tr>
</tbody>
</table>
values lead to higher probabilities and the individual datum proceeds to the next generation. Crossover was performed by two-point crossover to the selected pairs with a crossover probability. The partial chromosome of the selected pairs are exchanged between the two cross points, which are randomly set in two individual coding strings. During mutation, a mutation probability was used for another allele to replace a given allele, and then a new individual was created. Mutation sustains the diversity of population and prevents appearance of premature phenomenon. Since global search and local search are separately decided by crossover and mutation, good search performance leads to completion of the optimization procedure.

CASE STUDY

The TGR

The TGR, which is used for flood control, power generation, and navigation, is a vital project for water resource development of China’s largest tributary, the Yangtze River (Figure 5). The control catchment area of the TGR is 1 million km², accounting for 56% of the basin area of the Yangtze River and 49% of annual run-off volume, $4.51 \times 10^{11}$m³. The TGR is a typical, river channel-type reservoir and has a length of ∼570–650 km, an average width of ∼1.1 km, a mean annual discharge of $1.43 \times 10^4$ m³/s and a storage coefficient of approximately 3.7%. The normal water level of the TGR is 175 m and the corresponding total reservoir storage capacity is $3.93 \times 10^{10}$ m³. The limited water level is 145 m and the corresponding flood control storage is $2.215 \times 10^{10}$ m³. The structures of the project are designed based on the 1000 year flood condition and checked by 10,000 year flood plus 10%. With 32 installed sets of hydroelectric generating 700 MW each, the annual power generation achieves $1.0 \times 10^{11}$ kW, and the total installed capacity is up to $2.25 \times 10^7$ kW.

Ensemble-based hydrologic forecasts

The ANFIS model was set up to estimate the TGR inflow based on the input–output pattern. With the time interval of one day, 1,840 data sets of flood season (from June to September) from 2006 to 2010 were used. These data were divided into three independent subsets: the training, validating, and testing subsets. The training subset included the

Figure 5 | Sketched map of the TGR (quoted from Liu et al. 2015).
The training subset was used to generate the initial FIS and to continuously correct FIS structure parameter for optimization. The validating subset was used to avoid model overfitting and the testing subset was used to examine if the FIS property meet the desired requirements. A multiple inputs and single output model was used when input variables were the main upstream inflow (Cuntan gage station), the tributary inflow (Wulong gage station), and the average daily rainfall from the TGR intervening basin. Several forecasting scenarios were chosen by changing the type of membership function, clustering method and the manner for training of the FIS.

The criteria of the Nash–Sutcliffe model efficiency index $R^2$ (Nash & Sutcliffe 1970) and the mean relative error of the volumetric (RE) were used for evaluating the ANFIS model. These are defined as:

\[
R^2 = \left[1 - \frac{\sum (Q_t - \hat{Q}_t)^2}{\sum (Q_t - \bar{Q})^2}\right] \times 100\% \tag{24}
\]

\[
RE = \frac{\sum (Q_t - \hat{Q}_t)}{\sum Q_t} \times 100\% \tag{25}
\]

where $Q_t$ is the observed value at $t$ step, $\hat{Q}_t$ is the forecasted value at the $t$ step, and $\bar{Q}$ is the mean value of $Q_t$ at the training, validating, or testing period. The ANFIS produced suitable results after employing the criteria of $R^2$ and RE for inflow forecasting in all three different data sets as shown in Table 2.

### RESULTS AND DISCUSSION

The ANFIS produced acceptable results after using the $R^2$ and RE criteria for the TGR inflow forecasting in all three different data sets as shown in Table 2. If $R^2$ is equal to 1 and RE is equal to 0, these two phenomena mean that the forecasted and observed results perfect fit. The ANFIS produces a low RE and a high $R^2$ for the inflow forecasting and the results of $R^2$ and RE are very close to 1 and 0, respectively, in all three data sets. This suggests that ANFIS is an accurate and stable forecasting method.

When compared with the traditional optimum operation, good results were obtained with the defined risk constraints. Figure 6 shows the comparison between the operated water level and the optimum water level from 10–16 June, 2010 during the flood season. Comparing the operated release and the optimum release in Figure 7, the optimum release was a flat discharge, which enhanced the optimized water level, as shown in Figure 7. This can be rationalized by the water quantity equilibrium equation, which states that the water level increases, because the release is less than the inflow and vice versa. According to the risk constraint indices of Equations (22) and (23), the GA was used in the optimum operation of the TGR. As shown in Table 3 and Figure 8, the operated hydropower produces $7.71 \times 10^7$ kW of hydropower with a flood risk of 3.46%, which is acceptable since the designed flood risk is 5%. Conversely, the optimum hydropower output has a flood risk of 4.65% and produces $8.15 \times 10^7$ kW of hydropower. In fact, the optimum hydropower generation was increased by 5.7% compared with the normal operated hydropower generation. This increase reveals that raising...
the water level and reducing water release is important for increasing the water head to provide abundant hydropower generation at safe levels. Additionally, the end water level is higher than the operated one, which means more energy is available to produce power under the conditions where the risks are controlled within acceptable value (5%).

Table 3 | Risks and profits of two schemes for the 2010 floods

<table>
<thead>
<tr>
<th>Schemes</th>
<th>Reservoir risk (%)</th>
<th>Hydropower generation (10⁷kW)</th>
<th>End water level (m)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Operated scheme</td>
<td>3.46</td>
<td>7.71</td>
<td>145.58</td>
</tr>
<tr>
<td>Optimized scheme</td>
<td>4.65</td>
<td>8.15</td>
<td>146.01</td>
</tr>
</tbody>
</table>

Figure 6 | Comparison of water levels from 10–16 June 2010.

Figure 7 | Comparison of releases from 10–16 June 2010.
CONCLUSIONS

In this study the risk constraints and an intelligent algorithm for optimum operation of the TGR are discussed with the ensemble-based hydrologic forecasting of the inflow from 10–16 June during the flood season in 2010. The following are the conclusions.

(1) As a result of the capability of learning, constructing, expensing, and classifying, ANFIS was used to forecast the TGR water inflow. Accurate and stable forecasting results were obtained, because the criteria of $R^2$ and RE are very close to 1 and 0, respectively. This is the pre-condition for the optimum operation of the TGR with defined risk constraints.

(2) In this study, GA was used for the TGR optimization operation. The novel risk constraint indices were added into the optimum operation. Under optimum operation, the end water level increased to 146.01 m and hydropower generation increased by 5.7% with a flood risk of 4.65%, which is within the controlled range (<5%). Therefore, the proposed forecasting method for optimizing the operation of the TGR, which enhances hydropower generation within acceptable risk constraints, is feasible.

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