Selection of criteria for multi-criteria decision making of reservoir flood control operation

Feilin Zhu, Ping-an Zhong, Yimeng Sun and Bin Xu

ABSTRACT

In reservoir flood control operation, selection of criteria is an important part of the multi-criteria decision making (MCDM) procedure. This paper proposes a method to select criteria for MCDM of reservoir flood control operation based on the back-propagation (BP) neural network. According to the concept of ideal and anti-ideal points, we propose a method to generate training samples of the BP neural network via stochastic simulation. The topological structure of a three-layer BP neural network used for criteria selection is established. The relative importance of criteria is derived via the learned connection weights of a trained BP neural network, and its calculation method is proposed. The sensitivity curve method is employed to conduct sensitivity analysis, and the relative contribution ratio is defined to quantify the relative sensitivity strength of each criterion. We present the principle and threshold value of criteria selection based on the comprehensive discrimination index defined by the combination of the relative importance and relative contribution ratio. The Pubugou reservoir is selected as the case study. The results show that the proposed method can provide an effective tool for decision makers to select criteria before MCDM modeling of reservoir flood control operation.

Key words | back-propagation (BP) neural network, multi-criteria decision making, reservoir flood control operation, selection of criteria, threshold value

Feilin Zhu
Ping-an Zhong (corresponding author)
Yimeng Sun
Bin Xu
College of Hydrology and Water Resources,
Hohai University,
No. 1 Xikang Road,
Nanjing 210098,
China
E-mail: *pazhong@hhu.edu.cn*

Ping-an Zhong
National Engineering Research Center of Water Resources Efficient Utilization and Engineering Safety,
Hohai University,
No. 1 Xikang Road,
Nanjing 210098,
China

Yimeng Sun
State Key Laboratory of Hydrology Water Resources and Hydraulic Engineering,
Hohai University,
No. 1 Xikang Road,
Nanjing 210098,
China

INTRODUCTION

Reservoir flood control operation is an important non-engineering measure in the flood management of river basins, which is complicated in nature because it involves many conflicting factors resulting from technical, environmental, social and political concerns (Chou & Wu 2015). Reservoir flood control operation needs to simultaneously optimize several incommensurable and often conflicting objectives, such as flood control, water supply, hydropower generation, navigation, irrigation, ecology and so on. It is impractical or even impossible to obtain a single optimal solution that simultaneously optimizes all of these objectives due to the presence of multiple conflicting objectives (Cheng & Chau 2001; Qin *et al.* 2010; Malekmohammadi *et al.* 2011). Instead, a more practical way is to generate some feasible non-inferior alternatives in advance by multi-objective optimization models (Ouyang *et al.* 2014; Luo *et al.* 2015), then a multi-criteria decision making (MCDM) model is used to rank these non-inferior alternatives against multiple criteria so that the preferred alternative can be determined and the final flood control decision can be made. Generally, the MCDM process of reservoir flood control operation comprises the following steps: (1) generate alternatives using flood control operation models; (2) select criteria; (3) calculate the performance values of alternatives against the selected criteria; (4) weight the criteria; (5) rank the alternatives via MCDM models; (6) perform sensitivity analysis; (7) make the final decision (Hajkowicz & Collins 2007).

doi: 10.2166/hydro.2017.059

Numerous methods have been developed to solve MCDM problems since the 1960s. Hajkowicz & Collins (2007) classified these methods into six categories: (1) multi-criteria value functions; (2) outranking approaches; (3) distance to ideal point methods; (4) pairwise comparisons; (5) fuzzy set analysis; (6) tailored methods. In recent years, many researchers have also proposed new MCDM methods or improved the existing techniques, and applied them in the field of reservoir flood control operation (Cheng & Chau 2001, 2002; Chen & Hou 2004; Yu et al. 2004; Fu 2008; Wang et al. 2011; Zhu et al. 2016a, 2016b). In the MCDM of reservoir flood control operation, criteria are typically employed to measure the performance of each alternative from different aspects, such as utilization efficiency of flood resources, flood control safety of reservoirs and downstream protected regions, etc. Selection of criteria is referred to structuring the MCDM problems, and is the most important part of MCDM in view of the fact that selected criteria will directly influence the MCDM results (Howard 1991; Hajkowicz & Collins 2007; Durbach & Stewart 2012; Wang et al. 2014). Traditionally, the criteria are selected only via subjective judgments and then used for MCDM modeling directly (Cheng & Chau 2001, 2002; Chen & Hou 2004; Yu et al. 2004; Fu 2008; Wang et al. 2011). The selection of criteria mentioned here does not refer to this subjective way of selection, but a comprehensive and quantitative examination of criteria. During the selection process, the criteria should be examined from two aspects. Firstly, each criterion has different contributions to the final MCDM results, namely, each criterion has inherently different degrees of importance. Some criteria may contribute more to the MCDM results, while some criteria may contribute less. Secondly, changes in the value of each criterion may lead to different responses of MCDM results, that is, the MCDM results have different sensitivity strength to each criterion. Before MCDM modeling, those criteria with a small importance degree and sensitivity strength can be regarded as redundant criteria and should not be selected, because they do not strongly influence the MCDM results. Although plenty of methods are available to solve an MCDM problem of reservoir flood control operation once it has been structured, little attention has been paid to help decision makers select criteria in the first place.

The back-propagation (BP) neural network is one kind of the most widely applied feedforward neural networks, in which a gradient descent algorithm is used for network training (Hassoun 1995). The BP neural network is a distributed information processing system with the ability to store experiential knowledge obtained by network learning and make it available for future use (Parasuraman et al. 2006). BP neural networks allow nonlinear mapping between inputs and outputs. Inputs are weighted and processed through nodes. Networks are commonly trained using the error-back propagation algorithm by adjusting connection weights to minimize errors between network outputs and target outputs. Therefore, information about the system is finally stored in connection weights. In this paper, we study the network's weights to assess the relative importance of inputs.

This paper aims to propose a method to select criteria for MCDM of reservoir flood control operation based on the BP neural network. The novel aspects and main contributions of this study are as follows: (1) the method to generate training samples of the BP neural network is developed based on the concepts of ideal and anti-ideal points; (2) the topological structure of the BP neural network used for criteria selection is established; (3) definitions and calculation methods for the relative importance and relative contribution ratio of criteria are proposed; (4) the principle and threshold value of criteria selection are presented.

The rest of this paper is organized as follows. The 'Methodology' section consists of five subsections: (1) generating training samples of the BP neural network; (2) designing the topological structure of the BP neural network; (3) identifying the relative importance of criteria; (4) sensitivity analysis; (5) principle of criteria selection. The next section presents the results of a case study using the proposed methodology, followed by discussions and conclusions in the final section.

METHODOLOGY

Generating training samples of the BP neural network

The core of criteria selection is to enable BP neural networks to evaluate flood control operation alternatives as MCDM models, and this can be achieved through network training. The training process of the BP neural network aims to establish a nonlinear mapping between the input and output layer so that each input vector can produce output values that are as close as possible to the target output desired.

The concept of ideal and anti-ideal points has been widely employed to solve MCDM problems according to the principle that the best alternative should be the one as close as possible to the ideal alternative and as far as possible from the anti-ideal alternative. The so-called ideal and anti-ideal alternatives are not real alternatives which are physically meaningful, but suppositional alternatives used to characterize the upper and lower limit state of the alternative set (Hwang & Yoon 1981; Fu 2008). In this paper, the ideal and anti-ideal alternatives are also defined for flood control operation, based on this, we propose a method for generating training samples by randomly sampling criteria values between ideal and anti-ideal alternatives in order to meet the accuracy requirement of network training. Criteria values of the training samples are chosen as the network inputs, and the closeness coefficient (Hwang & Yoon 1981), which is usually used to rank alternatives, is selected as the comprehensive evaluation index, i.e., the network output. The following steps are involved:

1. Use flood control operation models to generate m mutually non-dominating alternatives, i.e., $\{x_{ij}|i = 1, 2, \cdots, m; j = 1, 2, \cdots, n\}$, where m and n represent the number of alternatives and criteria, respectively.
2. Determine the ideal alternative $\left\{x_j^+|j = 1, 2, \cdots, n\right\}$ and anti-ideal alternative $\left\{x_j^-|j = 1, 2, \cdots, n\right\}$. The ideal point contains the best values for each criterion from the set of alternatives while the anti-ideal point contains the worst values. They set the upper and lower limit state of all alternatives and are expressed as follows:

$$x_j^+ = \begin{cases} \max\limits_{1\le i\le m}\{x_{ij}\} & \text{For benefit or positive criteria} \\ \min\limits_{1\le i\le m}\{x_{ij}\} & \text{For cost or negative criteria} \end{cases} \tag{1}$$

$$x_j^- = \begin{cases} \min\limits_{1\le i\le m}\{x_{ij}\} & \text{For benefit or positive criteria} \\ \max\limits_{1\le i\le m}\{x_{ij}\} & \text{For cost or negative criteria} \end{cases} \tag{2}$$

3. Generate the input data of the BP neural network through stochastic simulation. Generate k random numbers following the uniform distribution $u_g \sim U(0, 1)$, g = 1, 2, …, k, the value of k can be determined according to the accuracy requirement of network training. For each simulation, a unique ug is used for all criteria. Randomly sample the criteria values between the ideal and anti-ideal alternatives by the following equation:

$$x_{gj} = x_j^+ - (x_j^+ - x_j^-) \times u_g \tag{3}$$

In addition, take the ideal and anti-ideal alternatives as two input data, then the input data of the BP neural network can be expressed as $\{x_{tj}|t = 1, 2, \cdots, p; j = 1, 2, \cdots, n\}$, where p is the sample size, $p = k + 2$.
4. Calculate the Euclidean distances from each training sample to the ideal and anti-ideal alternatives, as given by:

$$\begin{cases} d_t^+ = \sqrt{\sum\limits_{j=1}^{n}(x_j^+ - x_{tj})^2} \\ d_t^- = \sqrt{\sum\limits_{j=1}^{n}(x_j^- - x_{tj})^2} \end{cases} \tag{4}$$

5. Calculate the closeness coefficient ct by Equation (5). The closeness coefficient ct ranges between 0 and 1, and reflects the relative distance from the tth training sample to the ideal and anti-ideal alternatives. The larger the ct is, the tth training sample is closer to the ideal alternative and farther from the anti-ideal alternative, and then the better the tth training sample is.

$$c_t = \frac{d_t^-}{d_t^+ + d_t^-} \tag{5}$$

6. In order to avoid the influence of dimension differences to the network training accuracy, the input data are scaled to the range of [0, 1] by the linear normalization approach (Shi 2000), expressed as follows:

$$x_{tj}^* = \frac{x_{tj} - x_{j\min}}{x_{j\max} - x_{j\min}} \tag{6}$$

where x_{tj} and x_{tj}^* are the original and normalized input data, respectively; $x_{j\max}$ and $x_{j\min}$ are the maximum and minimum values within the original input data, respectively.

The normalized criteria values x_{tj}^* serve as the input data of the BP neural network, the closeness coefficient c_t is selected as the network output, and the final training sample set can be expressed as $\left\{x_{tj}^*, c_t | t = 1, 2, \cdots, p; j = 1, 2, \cdots, n\right\}$.

Designing the topological structure of the BP neural network

The BP neural network consists of an input layer, one or more hidden layers and an output layer. The important issues in the establishment of topological structure include the determination of hidden layer numbers, the number of hidden neurons (nodes) and the activation function. Kolmogorov theorem has proved that the BP neural network with a single hidden layer can approximate any continuous differentiable function and establish a nonlinear mapping between the input and output layer. Therefore, this study establishes a three-layer BP neural network, the topological structure is illustrated in Figure 1. The number of neurons in the input layer corresponds to the number of criteria, and the input data are the normalized criteria values. The output layer comprises only one neuron, and the target output is the closeness coefficient of each training sample.

One of the important issues in developing a BP neural network is the determination of the appropriate number of hidden neurons that can satisfactorily capture the nonlinear relationship existing between the input variables and the output (Parasuraman et al. 2006). The number of hidden neurons is usually determined by trial and error method with the objective of minimizing the cost function. In real-world applications, the trial and error method has a large computational burden and is time-consuming. Besides, many empirical formulas are available to determine the number of hidden neurons. In order to avoid extra computational burden, this study uses the empirical formula recommended by Lippmann (1987) to determine the number of hidden neurons, i.e., $h = 1 \times (n+1)$.

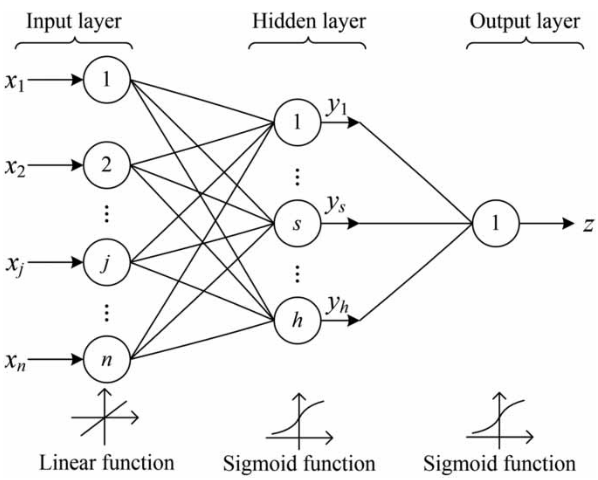

Figure 1 | Schematic diagram of the three-layer BP neural network.

The input, hidden and output layers are connected in sequence with connection weights that determine the strengths of the unidirectional connections. Symbolically, the architecture shown in Figure 1 can be represented as BP (n: h: 1). The commonly used activation functions include linear, sigmoid and hyperbolic tangent function. The established BP neural network makes use of the linear function in the input layer, and uses the sigmoid function in the hidden and output layer. During the training process, the connection weights are updated systematically by using the error-back propagation algorithm and gradually converge to values such that each input vector produces output values that are as close as possible to the target output. The actual output is compared with the target output, then the global error of the network is calculated by Equation (7). The training process stops until the prescribed training times or the error tolerance is reached.

$$E = \sum_{t=1}^{p} \frac{(z_t - c_t)^2}{2} \tag{7}$$

where z_t and c_t are actual and target output of the tth training sample, respectively.

Identifying the relative importance of criteria

The BP neural network is commonly trained by adjusting connection weights to minimize errors between network outputs and target outputs. Therefore, for a trained BP neural network, information about the system is finally stored in connection weights. In this section, we propose a method to identify the relative importance of criteria from a trained BP neural network via the learned connection weights.

As shown in Figure 1, the input vector is expressed as $X = (x_1, x_2, \cdots, x_j, \cdots, x_n)^T$, the output vector of the hidden layer is expressed as $Y = (y_1, y_2, \cdots, y_s, \cdots, y_h)^T$, z represents the actual output of the BP neural network. The jth input neuron and sth hidden neuron are connected with the connection weight w_{js}. Similarly, w_s is the connection weight between the sth hidden neuron and the output neuron. Parameters θ_s and θ represent the bias of corresponding neurons in the hidden and output layer, respectively. The initial connection weights and biases are given randomly from the range $(-1, 1)$. The inputs are transformed to output by the following equations:

$$y_s = f(\beta_s) = f(\sum_{j=1}^{n} w_{js}x_j + \theta_s) \tag{8}$$

$$z = f(\alpha) = f(\sum_{s=1}^{h} w_s y_s + \theta) \tag{9}$$

where β_s represents the inputs of the hidden layer; α is the inputs of the output layer; $f(\cdot)$ is the sigmoid function, i.e., $f(x) = 1/(1 + e^{-x})$, and $f'(x) = f(x)(1 - f(x))$.

The importance degree of the jth criterion to the network output is derived by the partial derivative of actual output z to the jth component of the input vector X, shown as follows:

$$\begin{aligned}
\frac{\partial z}{\partial x_j} &= \frac{\partial z}{\partial \alpha}\frac{\partial \alpha}{\partial x_j} = f(\alpha)(1 - f(\alpha))\frac{\partial \sum_{s=1}^{h}(w_s y_s + \theta)}{\partial x_j} \\
&= f(\alpha)(1 - f(\alpha))\sum_{s=1}^{h} w_s \frac{\partial y_s}{\partial x_j} \\
&= f(\alpha)(1 - f(\alpha))\sum_{s=1}^{h} w_s \frac{\partial y_s}{\partial \beta_s}\frac{\partial \beta_s}{\partial x_j} \\
&= f(\alpha)(1 - f(\alpha))\sum_{s=1}^{h} w_s f(\beta_s)(1 - f(\beta_s))\frac{\partial \sum_{j=1}^{n}(w_{js}x_j + \theta_s)}{\partial x_j} \\
&= f(\alpha)(1 - f(\alpha))\sum_{s=1}^{h} f(\beta_s)(1 - f(\beta_s))(w_{js}w_s)
\end{aligned} \tag{10}$$

For a given input vector X, $f(\alpha)$ and $f(\beta_s)$ in Equation (10) are constants. Comparing the importance degree of the jth criterion and $(j+1)$th criterion:

$$\frac{\partial z}{\partial x_j} \Big/ \frac{\partial z}{\partial x_{j+1}} = \sum_{s=1}^{h}(w_{js}w_s) \Big/ \sum_{s=1}^{h}(w_{(j+1)s}w_s) \tag{11}$$

It can be seen from Equation (11) that the connection weights directly decide the relative importance between criteria. Therefore, we define the relative importance of the jth criterion R_j as follows:

$$R_j = \sum_{s=1}^{h}|w_{ds}w_s| \Big/ \sum_{d=1}^{n}\sum_{s=1}^{h}|w_{ds}w_s| \tag{12}$$

Considering that the initial connection weights are given randomly before network training, the learned connection weights and the calculated R_j always show slight differences during each training cycle. Consequently, the mean value of R_j (denoted by $\overline{R_j}$) is used to represent the relative importance of the jth criterion as follows:

$$\overline{R_j} = \frac{1}{N}\sum_{l=1}^{N} R_j^l \tag{13}$$

where N is the total number of training times; R_j^l is the relative importance of the jth criterion during the lth training cycle.

The larger the value of $\overline{R_j}$, the more the jth criterion contributes to the MCDM results, making it inherently more important than the other criteria.

Sensitivity analysis

In this section, we used the closeness coefficient equation (i.e., Equation (5)) to conduct sensitivity analysis, and quantified the relative contribution ratio of criteria changes to the change of MCDM results.

Plenty of sensitivity analysis approaches, such as the method of Morris (Morris 1991), the Sobol' sensitivity analysis (Sobol' 2001) and so on, are available to assess the impact of one variable to model outputs. In this paper, a simple but practical method, sensitivity curve method (Paturel et al. 1995), is used to calculate and plot the relative changes of an input variable against the relative changes of the closeness coefficient. The sensitivity curve method is similar to the method of Morris, which is a so-called one-step-at-a-time method, meaning that in each run only one criterion is given a new value and other criteria remain at their original values. The procedures of conducting the sensitivity analysis can be described as follows:

(1) Assume the original input vector is $X = (x_1, x_2, \cdots, x_j, \cdots, x_n)^T$. For the value of the jth criterion (denoted as x_j), we set nine scenarios for changes in x_j by adjusting x_j via delta changes, i.e., $x_j* = x_j(1 + \Delta x_j)$, $\Delta x_j = 0, \pm 5\%, \pm 10\%, \pm 15\%, \pm 20\%$.
(2) The corresponding new input vector is expressed as $X^* = (x_1, x_2, \cdots, x_j^*, \cdots, x_n)^T$. Then, the closeness coefficient is recalculated (denoted as $\bar{c}$) under each changing scenario.
(3) The relative changes of each criterion against the relative changes of the closeness coefficient are calculated and plotted as sensitivity curves.

In order to quantify the relative contribution ratio of each criterion, the absolute change of the closeness coefficient is expressed as $\Delta c_j = |c - \bar{c}|$ when $\Delta x_j = +20\%$ (c is the original closeness coefficient). Then the relative change is expressed as:

$$\Delta c_j* = \frac{\Delta c_j}{c} \tag{14}$$

The relative contribution ratio of the jth criterion is defined as:

$$G_j = \frac{\Delta c_j*}{\sum_{j=1}^{n} \Delta c_j*} \times 100\% \tag{15}$$

The relative contribution ratio measures the relative influence of criteria changes to the closeness coefficient, namely, the relative sensitivity strength of MCDM results to each criterion. The larger the G_j, the stronger the relative sensitivity of the jth criterion. Therefore, those criteria with large G_j should be selected for MCDM modeling.

Principle of criteria selection

The relative importance and relative contribution ratio introduced above can reveal valuable information about the degree of importance and sensitivity strength of criteria, and provide necessary references for decision makers to select appropriate criteria for MCDM modeling. During the criteria selection process, each criterion needs to be examined in terms of the relative importance and relative contribution ratio, which may make decision makers feel perplexed to select criteria via subjective judgment due to the fact that some criteria may have a large relative importance but a small relative contribution ratio. Consequently, it is necessary to establish the principle and threshold value for criteria selection. Here we define the comprehensive index F_j, which combines the relative importance and relative contribution ratio via a multiplying operator as follows:

$$F_j = \overline{R_j} \times G_j \tag{16}$$

where $\overline{R_j}$ and G_j are the relative importance and relative contribution ratio of the jth criterion, respectively. $\overline{R_j}$ and G_j range from 0 to 1, so the use of multiplying operator can make the comprehensive index easier to be discriminated.

The criteria with a large F_j should be selected for MCDM modeling, while the criteria with a small F_j should be deleted from the original criteria system. The priority of deleting criteria can be determined according to the value of F_j, that is, the criteria with a smaller F_j should be deleted earlier. Particularly, if the value of F_j is smaller than the mean value of all criteria (denoted by $\overline{F_j}$) over one order of magnitude, the relative importance and relative contribution ratio of this criterion are considered significantly smaller than the average level of all criteria and the criteria should be deleted from the original criteria system. In order to quantify the logical judgment process, the comprehensive discrimination index of the jth criterion is defined as:

$$P_j = \lg \frac{F_j}{\overline{F_j}} \tag{17}$$

The comprehensive discrimination index can reflect the difference between the order of magnitude of F_j and $\overline{F_j}$. If $P_j > 0$, the jth criterion's F_j is larger than the average level; if $P_j < 0$, the jth criterion's F_j is smaller than the average level; particularly, if $P_j \leq -1$, the jth criterion's F_j is significantly smaller than the average level over one order of magnitude, and this criterion should be deleted from the original criteria system. Therefore, we choose $P_j \leq -1$ as the threshold value of criteria selection, this threshold value can avoid the influence of criteria selection on MCDM results, but it cannot guarantee the original criteria system to be simplified to the greatest extent. This paper tries to transform the criteria selection process from subjective judgment to quantitative calculation process, however, subjectivity is still unavoidable when choosing the appropriate threshold value of criteria selection. In real-world applications, we can determine the ultimate threshold value by decreasing the threshold value step by step until a change of MCDM results occur.

CASE STUDY

Overview of the Pubugou reservoir

The case study is conducted in the Pubugou reservoir which is a key flood control project located in the Daduhe River basin in China. The Daduhe River basin is one of the main tributaries of the Yangtze River and covers an area of 90,000 km^2. Floods, mainly caused by rainfall, occur frequently during the flood season from June to August. The Pubugou reservoir is built for multiple purposes including flood control, hydropower generation, irrigation, water supply and navigation. The total storage capacity, flood limited water level, design flood water level and check flood control water level are 5.06 billion m^3, 841.00 m, 850.24 m and 853.78 m, respectively. The Leshan city is located at the downstream of the Pubugou reservoir, which is an important flood control protected region with a population size of 3,544,000 and GDP of 113.48 billion CNY. Locations of the Daduhe River basin, the Pubugou reservoir and the Leshan city are shown in Figure 2.

Establishment of the original criteria system

In reservoir flood control operation, decision makers are required to schedule releases considering the safety of reservoirs, the safety of downstream protected regions and flood resources utilization efficiency. Under the premise of flood control safety, the overall benefits should be maximized as much as possible. Due to the fact that it is difficult to quantify flood damage (e.g., economic loss, population impacted, etc.) especially for the real-time scale, flood control target factors (e.g., the highest water level, the terminal water level, the peak discharge of outflow and etc.) are usually chosen as criteria to assess alternatives instead of using flood damage directly (Yu et al. 2004; Fu 2008; Wang et al. 2011; Zhu et al. 2016a).

In this case study, we establish the original criteria system consisting of 10 criteria. This first criterion is the difference between the check flood water level and the highest water level (denoted as Z_{ch}–Z_{max}), which is used to reflect the reservoir's own safety during flood control operation. The terminal water level is an important criterion used to balance flood control and hydropower generation, a large value of the terminal water level is beneficial to hydropower generation but will lead to future flood control risks, while a small value corresponds to a large flood control storage for future use but will result in a low productive head for hydropower generation. Dynamic control of flood limited water level has been found to be an effective way to increase hydropower generation without causing extra flood control risks during flood seasons (Li et al. 2010; Ding et al. 2015). In this case study, the difference between the terminal water level and ideal water level (denoted as Z_e–Z_{id}) is chosen as a second criterion, and the ideal water level (Z_{id}) equals the flood limited water level, i.e., $Z_{id} = 841.00$ m. Furthermore, we use the volume of abandoned water (denoted as W_{ab}) to reflect the wasting degree of flood resources. The peak discharge in the downstream flood control section (denoted as Q_{max}) is chosen to reflect the safety of the downstream protected regions. The duration of reservoir outflow exceeding the safety discharge in the downstream flood control section (denoted as T) is used to reflect the duration of the downstream flood control section being damaged by the flood event. We use spillover volume exceeding the safety discharge in the downstream flood control section (denoted as W_{ex}) to reflect the degree of the downstream flood control section being damaged by the flood event. Moreover, different operation alternatives may lead to different risks for both downstream flood the control section

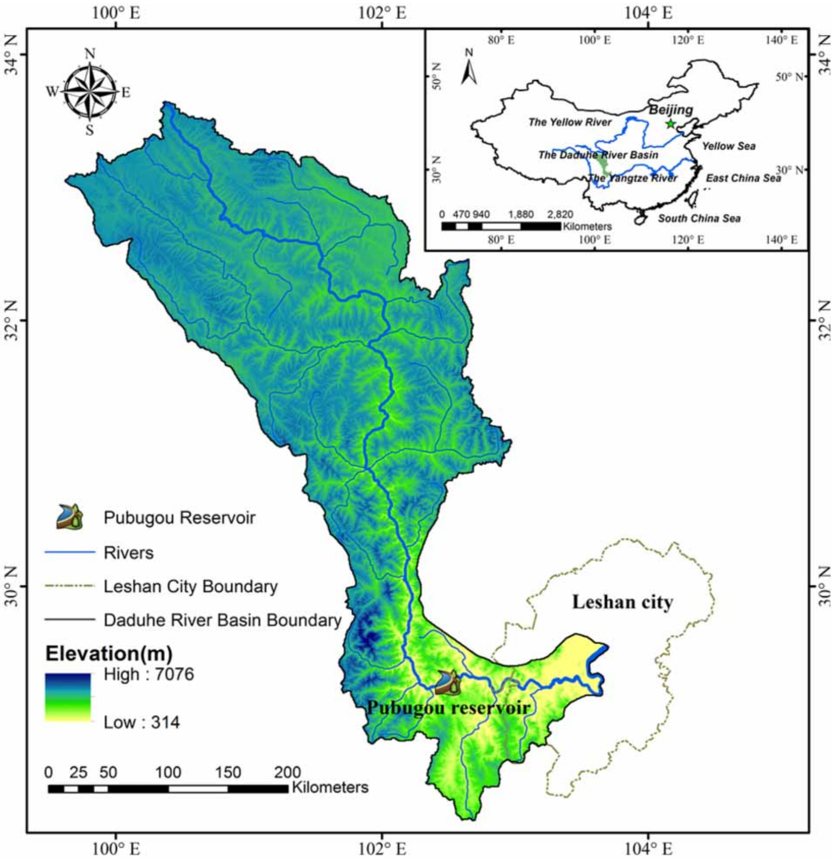

Figure 2 | Locations of the Daduhe River basin and the Pubugou reservoir.

and the reservoir itself. Therefore, we consider two criteria for the risk of failure of the dam and its structures (denoted as Z_f) as well as the risk of flooding in the downstream flood control section (denoted as Q_f). The risks (i.e., Z_f and Q_f) are calculated using the methods proposed by Chen et al. (2014). Due to the sediment problem, the flood control capability of the reservoir has been reduced to a great extent, thus in the flood control process, we should consider the sediment load (denoted as S_l) to expand the reservoir's life cycle. The Pubugou reservoir is also built for shipping, which requires the reservoir outflow to be as stable as possible. Therefore, we choose the standard deviation of outflows (denoted as Q_{sd}) as an initial criterion to measure the influence of different alternatives to shipping. Among all of the 10 criteria, Z_{ch}–Z_{max} is a benefit criterion, and other criteria are cost criteria.

In previous studies (Cheng & Chau 2001, 2002; Chen & Hou 2004; Yu et al. 2004; Fu 2008; Wang et al. 2011; Zhu et al. 2016a, 2016b), the criteria system is subjectively developed and used for MCDM modeling without conducting the criteria selection procedure. In this case study, we apply the proposed methodology to examine the relative importance and relative contribution ratio of each criterion, and further help decision makers to select appropriate criteria for MCDM modeling.

Generation of flood control operation alternatives

We establish a flood control optimization operation model based on the rule of maximum flood peak reduction to generate feasible flood control operation alternatives. The maximum flood peak reduction operation model aims to minimize the peak discharge of reservoir outflow as well as to mitigate the flood damage in the downstream flood control section. The objective function of the optimization operation model is formulated as follows:

$$\text{Minimize} \quad F = \sum_{t=1}^{T} (Q_{\text{out}}(t) + Q_e(t)) \tag{18}$$

where t and T are the time sequence and the number of time periods, $Q_{out}(t)$ is reservoir outflow, and $Q_e(t)$ represents the lateral inflow between the reservoir and Leshan city.

The constraints of the optimization operation model include water balance constraint, the highest water level constraint, terminal water level constraint, outflow limit constraint, and outflow variation limit constraint. These constraints are formulated below:

$$V(t) = V(t-1) + \left[\frac{Q_{in}(t) + Q_{in}(t-1)}{2} - \frac{Q_{out}(t) + Q_{out}(t-1)}{2}\right]\Delta t \tag{19}$$

$$Z(t) \leq Z_m(t) \tag{20}$$

$$Z_e = Z_{id} \tag{21}$$

$$Q_{out}(t) \leq Q_{\max}(t) \tag{22}$$

$$|Q_{out}(t) - Q_{out}(t-1)| \leq \nabla Q_m \tag{23}$$

where $V(t)$ represents the reservoir storage at time t, Δt is the time interval, $Z(t)$ and $Z_m(t)$ denote the water level and the upper limit of water level at time t, respectively, Z_e and Z_{id} represent the terminal water level and ideal water level, respectively, and ∇Q_m is the permissible outflow variation limit (500 m^3/s).

An actual flood event is used as the input to the flood control system consists of the Pubugou reservoir and Leshan city. The stepwise trial-and-error algorithm (Zhong *et al.* 2003) is employed to solve the established optimization operation model. By setting different upper limits of water level, 10 non-dominated flood control operation alternatives are generated and their criteria values are obtained after reservoir flood routing, as shown in Table 1.

Training the BP neural network

Based on the generated 10 alternatives, ideal and anti-ideal alternatives are determined using Equations (1) and (2). The criteria values are randomly sampled and normalized between the ideal and anti-ideal alternatives by Equations (3) and (6). Then the closeness coefficient is calculated through Equations (4) and (5), and 30 training samples are obtained, as shown in Table 2. The sample series from 1 to 25 are used for training, and the sample series from 26 to 30 are used for verification.

According to the number of original criteria and Figure 1, the architecture of the BP neural network is determined as BP (10: 11: 1). The main parameters of the

Table 1 | Criteria values of the 10 reservoir flood control operation alternatives

Alternative no.	Z_{ch}–Z_{max} (m)	Z_e–Z_{id} (m)	W_{ab} (10^6 m^3)	Q_{max} (m^3/s)	T (h)	W_{ex} ($10^6 m^3$)	Z_f	Q_f	S_l (t)	Q_{sd} (m^3/s)
1	4.78	5.44	1970	4810	51	40	0.28	0	290	508
2	5.28	5.10	2100	4880	56	48	0.13	0	277	561
3	5.78	4.58	2220	4940	59	54	0.08	0	260	614
4	6.28	4.02	2350	5020	66	61	0	0	250	667
5	6.78	3.46	2480	5090	72	70	0	0	237	720
6	7.28	3.06	2620	5180	76	74	0	0	224	773
7	7.78	2.45	2750	5270	83	82	0	0	211	826
8	8.28	2.11	2880	5350	87	90	0	0.09	198	879
9	8.78	1.62	2940	5450	91	100	0	0.16	183	932
10	9.28	1.20	3010	5520	96	120	0	0.32	170	985

Table 2 | Training samples of the BP neural network and the training results

		Inputs										Target outputs	Actual outputs
Sample no.		Z_{ch}–Z_{max} (m)	Z_e–Z_{id} (m)	W_{ab} (10^6 m^3)	Q_{max} (m^3/s)	T (h)	W_{ex} (10^6 m^3)	Z_f	Q_f	S_l (t)	Q_{sd} (m^3/s)	Closeness coefficient	
Training samples	1	6.09	4.21	2708	5314	83	97	0.2	0.23	255	847	0.286	0.269
	2	7.98	2.43	2272	5016	64	63	0.08	0.09	205	646	0.714	0.741
	3	5.86	4.42	2760	5350	85	101	0.21	0.24	261	871	0.246	0.222
	…	…	…	…	…	…	…	…	…	…	…	…	…
	24	9.05	1.41	2022	4846	53	44	0.01	0.02	176	532	0.95	0.914
	25	5.73	4.55	2792	5371	87	103	0.22	0.25	265	885	0.214	0.200
Verification samples	26	4.96	5.27	2968	5492	94	117	0.27	0.31	285	966	0.036	0.111
	27	7.66	2.73	2344	5066	67	69	0.1	0.12	213	680	0.636	0.666
	28	6.94	3.4	2511	5179	74	82	0.15	0.17	232	756	0.472	0.472
	29	9.05	1.41	2022	4846	53	44	0.01	0.02	176	532	0.95	0.918
	30	7.17	3.19	2459	5144	72	78	0.13	0.15	226	732	0.532	0.530

network include: 0.8 learning rate, 0.5 momentum factor, 0.0005 error tolerance, and 30,000 training cycles. First, based on the sample series from 1 to 25, the connection weights are updated systematically by the error-back propagation algorithm and gradually converge to values such that each input vector produces the output value that is as close as possible to the target output. Second, after the network training process, the criteria values of sample series from 26 to 30 are used as inputs of the trained network to forecast the closeness coefficient, the actual outputs and target outputs of the closeness coefficient are given in Table 2 and compared in Figure 3. According to Figure 3, in both training and verification periods, the trained BP neural network has very high fitting degrees between the actual and target outputs, the coefficients of determination are 0.981 and 0.968, respectively. The results show that the aforementioned method of generating training samples proposed can guarantee a high accuracy of network training. Furthermore, the trained network shows a good forecasting performance, namely, the highly nonlinear mapping between the criteria values and the closeness coefficient has already been established.

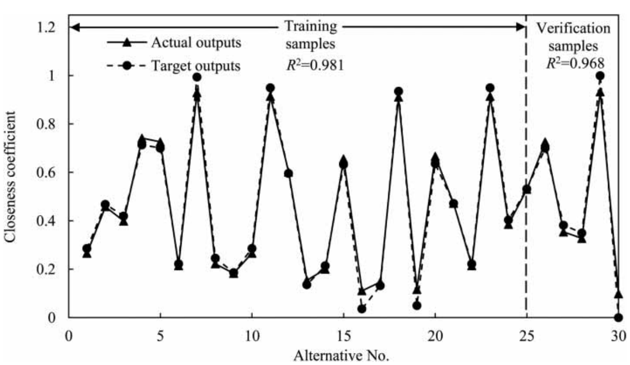

Figure 3 | Comparison between actual outputs and target outputs of the closeness coefficient.

Selection of criteria

Based on the trained network, the relative importance, relative contribution ratio and comprehensive discrimination index of each criterion are calculated through Equations (13), (15) and (17). Then, the initial criteria are selected according to the proposed threshold value, the results of criteria selection are listed in Table 3. Furthermore, the sensitivity analysis is implemented, and the relative changes of the closeness coefficient against the relative changes of the criteria values are plotted as sensitivity curves in Figure 4.

According to Table 3, the ranking of the relative importance is determined as: Z_{ch}–$Z_{max} > W_{ex} > Q_f > Z_f > Q_{max} > S_l > T > Z_e$–$Z_{id} > Q_{sd} > W_{ab}$. The ranking of the relative contribution ratio is: $Q_{max} > Z_{ch}$–$Z_{max} > Q_f > Z_f > W_{ab} > Q_{sd} > W_{ex} > T > S_l > Z_e$–$Z_{id}$. Furthermore, the ranking of the comprehensive discrimination index is then determined as: Z_{ch}–$Z_{max} > Q_f > Z_f > W_{ex} > Q_{max} > T > W_{ab} > Q_{sd} > S_l > Z_e$–$Z_{id}$. It can be seen from Table 3 that the comprehensive

Table 3 | Results of criteria selection

	Z_{ch}–Z_{max}	Z_e–Z_{id}	W_{ab}	Q_{max}	T	W_{ex}	Z_f	Q_f	S_l	Q_{sd}
$\overline{R_j}$	0.346	0.030	0.021	0.062	0.036	0.325	0.248	0.293	0.037	0.024
G_j	16.51%	3.50%	7.41%	24.80%	4.70%	5.41%	12.92%	14.91%	3.80%	6.04%
P_j	0.519	−1.217	−1.046	−0.051	−1.010	0.007	0.268	0.402	−1.090	−1.077
Decision	Select	Delete	Delete	Select	Delete	Select	Select	Select	Delete	Delete

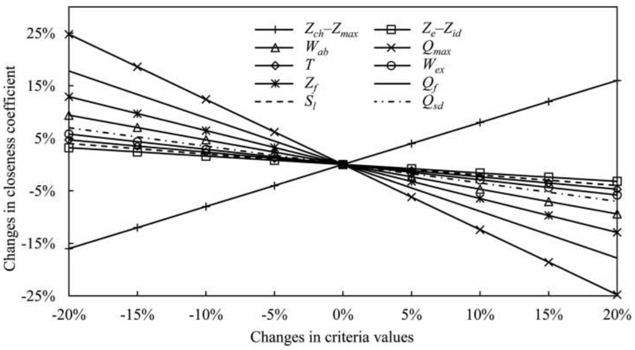

Figure 4 | Sensitivity analysis of closeness coefficient to the 10 criteria.

discrimination indices of five criteria (i.e., T; W_{ab}; Q_{sd}; S_l; Z_e–Z_{id}) are smaller than −1, indicating that the relative importance and relative contribution ratio of these five criteria can be considered significantly smaller than the average level of all criteria over one order of magnitude. According to the principle and threshold value of criteria selection, they should be deleted from the original criteria system. The comprehensive discrimination indices of the other five criteria (i.e., Z_{ch}–Z_{max}; Q_f; Z_f; W_{ex}; Q_{max}) are greater than −1 and these criteria should be selected for further MCDM modeling.

Rationality analysis of criteria selection

According to Table 3, it is reasonable to delete T, W_{ab}, Q_{sd}, S_l and Z_e–Z_{id}, because they get the worst performances on the relative importance as well as relative contribution ratio, and their comprehensive discrimination indices are smaller than the threshold value as well. The comprehensive discrimination indices of Z_{ch}–Z_{max}, Q_f and Z_f are greater than zero, indicating that the relative importance and relative contribution ratio of these three criteria are better than the average level of all criteria because they get relatively good performances on the relative importance and relative contribution ratio, therefore, it is reasonable to select these three criteria. It can be found that Q_{max} has a large relative contribution ratio but a small relative importance, while W_{ex} has a large relative importance but a small relative contribution ratio. Therefore, if we only examine the relative importance when selecting criteria, those criteria with large relative contribution ratios may be deleted by mistake, and vice versa. In this paper, we recommend using the comprehensive discrimination index, which combines both the relative importance and relative contribution ratio, for criteria selection.

In hydrological forecasting problems, forecasted results are usually compared with the benchmark results (i.e., the measures values) to test the performance of forecasting models (Zhu et al. 2016a). However, such a benchmark alternative in MCDM problems of flood control operation is difficult to determine to examine the effectiveness and rationality of the proposed methodology. Instead, multiple MCDM methods should be simultaneously used to test the sensitivity and rationality of the results (Hajkowicz & Collins 2007). Therefore, we use the TOPSIS model (Hwang & Yoon 1981), fuzzy matter-element model (Cai 1994) and fuzzy optimization model (Fu 2008) to evaluate the 10 flood control operation alternatives (listed in Table 1) simultaneously. These three models differ basically depending on how they: (1) determine marginal evaluation on each criterion; and (2) aggregate marginal evaluations across criteria to achieve a global evaluation (Durbach & Stewart 2012). The TOPSIS model determines the best alternative which is simultaneously closest to the ideal point and farthest from the anti-ideal point. The fuzzy matter-element model is a classical MCDM method based on the theory of matter element analysis. The fuzzy optimization model uses fuzzy ideal and anti-ideal weight distances to calculate fuzzy membership degrees, by which the rank of candidate alternatives are determined directly without a need to compare fuzzy numbers. The original criteria system and the selected criteria system are used as the inputs of the three MCDM models, and each criterion is assigned with equal weight. The MCDM results of the three models before and after criteria selection are compared in Table 4. It can be seen from Table 4 that all these three MCDM models get consistent ranking orders of the 10 alternatives before and after criteria selection. The results demonstrate that deleting T, W_{ab}, Q_{sd}, S_l and Z_e–Z_{id} does not influence the MCDM results because these criteria are inherently unimportant to the MCDM results as well as having a weak sensitivity. Before selection, some criteria may be highly correlated and measure the same underlying factor, this may be another reason for deleting some criteria without changing the MCDM results.

DISCUSSION AND CONCLUSIONS

In reservoir flood control operation, candidate alternatives are ranked through MCDM approaches, and selecting criteria is the most important part of the MCDM process. This paper proposed a method to select criteria for MCDM of reservoir flood control operation based on the BP neural network. The main conclusions are summarized as follows.

Based on the concepts of ideal and anti-ideal points, we proposed a method to generate training samples of the BP neural network via stochastic simulation. The topological structure of a three-layer BP neural network used for criteria selection was established. The relative importance of criteria was derived via the learned connection weights of a trained BP neural network, and its calculation method was proposed.

The sensitivity curve method was employed to conduct sensitivity analysis, and the relative contribution ratio was defined to quantify the relative sensitivity strength of each criterion.

The principle and threshold value of criteria selection were presented based on the comprehensive discrimination index defined by the combination of the relative importance and relative contribution ratio.

We applied the proposed methodology to a case study. The original criteria system consisting of 10 criteria was established. Then, the flood control optimization operation model based on the rule of maximum flood peak reduction was developed to generate 10 flood control operation alternatives. The results from the case study indicate that the method of generating training samples via stochastic simulation can guarantee a high accuracy of network

Table 4 | Comparison between MCDM results before and after criteria selection using three MCDM models

	TOPSIS model				Fuzzy matter-element model				Fuzzy optimization model			
	Before		After		Before		After		Before		After	
Alternative no.	c_i	Rank	c_i	Rank	ρH_i	Rank	ρH_i	Rank	u_i	Rank	u_i	Rank
1	0.515	9	0.508	9	0.215	9	0.201	9	0.480	9	0.488	9
2	0.698	7	0.698	7	0.398	7	0.372	7	0.584	7	0.591	7
3	0.784	5	0.786	5	0.486	5	0.492	5	0.671	5	0.683	5
4	0.892	1	0.889	1	0.628	1	0.644	1	0.739	1	0.742	1
5	0.887	2	0.884	2	0.593	2	0.602	2	0.734	2	0.736	2
6	0.880	3	0.881	3	0.581	3	0.571	3	0.730	3	0.731	3
7	0.872	4	0.871	4	0.561	4	0.510	4	0.723	4	0.726	4
8	0.772	6	0.772	6	0.443	6	0.451	6	0.643	6	0.651	6
9	0.658	8	0.666	8	0.329	8	0.318	8	0.555	8	0.562	8
10	0.499	10	0.492	10	0.183	10	0.162	10	0.398	10	0.412	10

Note: c_i, ρH_i and u_i represent the comprehensive evaluation index of TOPSIS model, fuzzy matter-element model and fuzzy optimization model, respectively.

training. The relative importance based on the learned connection weights can provide valuable information about the inherent contribution of each criterion to the MCDM results. This paper transforms the criteria selection process from subjective judgment to quantitative calculation process, and provides an effective tool for decision makers to select criteria before MCDM modeling of reservoir flood control operation.

It should be mentioned that the case study performed in the flood control system consists of a single reservoir and a single flood control section. However, compared with multi-reservoir systems, the original criteria system will be more complicated since more criteria are required to assess the performances of candidate alternatives, and the complexity will increase with the increasing number of reservoirs. Consequently, for large-scale multi-reservoir systems, the proposed methodology may have more effective applications to select appropriate criteria for MCDM modeling, which can further reduce the dimensionality of the original criteria system and simplify the MCDM modeling process.

ACKNOWLEDGEMENTS

This study was supported by the National Natural Science Foundation of China (Grant No. 51579068), the Special Fund for Public Welfare Industry of the Ministry of Water Resources of China (Grant No. 201501007), the Major Science and Technology Program for Water Pollution Control and Treatment (Grant No. 2014ZX07405002), the Fundamental Research Funds for the Central Universities (Grant No. 2017B40614; 2016B40214; 2015B05414), and the Research Innovation Program for College Graduates in Jiangsu Province of China (Grant No. KYLX16_0738; KYZZ15_0135). The first author was also supported by a fellowship from the China Scholarship Council for his visit to the University of California, Los Angeles.

REFERENCES

Cai, W. 1994 *Matter Element Model and its Application. Science and Technology Literature Press.* Science and Technology Literature Press, Beijing (in Chinese).

Chen, S. Y. & Hou, Z. C. 2004 Multicriterion decision making for flood control operations: theory and applications. *J. Am. Water. Resour. As.* **40**, 67–76.

Chen, J., Zhong, P. A., Xu, B. & Zhao, Y. F. 2014 Risk analysis for real-time flood control operation of a reservoir. *J. Water Resour. Plan. Manage.* **141**, 1–13.

Cheng, C. T. & Chau, K. W. 2001 Fuzzy iteration methodology for reservoir flood control operation. *J. Am. Water. Resour. As.* **37**, 1381–1388. doi:10.1111/j.1752-1688.2001.tb03646.x.

Cheng, C. T. & Chau, K. W. 2002 Three-person multi-objective conflict decision in reservoir flood control. *Eur. J. Oper. Res.* **142**, 625–631. doi:10.1016/S0377-2217(01)00319-8.

Chou, F. N. F. & Wu, C. W. 2015 Stage-wise optimizing operating rules for flood control in a multi-purpose reservoir. *J. Hydrol.* **521**, 245–260. doi:10.1016/j.jhydrol.2014.11.073.

Ding, W., Zhang, C., Peng, Y., Zeng, R. J., Zhou, H. C. & Cai, X. M. 2015 An analytical framework for flood water conservation considering forecast uncertainty and acceptable risk. *Water Resour. Res.* **51**, 4702–4726. doi:10.1002/2015WR017127.

Durbach, I. N. & Stewart, T. J. 2012 Modeling uncertainty in multi-criteria decision analysis. *Eur. J. Oper. Res.* **223**, 1–14. doi:10.1016/j.ejor.2012.04.038.

Fu, G. T. 2008 A fuzzy optimization method for multicriteria decision making: an application to reservoir flood control operation. *Expert Syst. Appl.* **34**, 145–149. doi:10.1016/j.eswa.2006.08.021.

Hajkowicz, S. & Collins, K. 2007 A review of multiple criteria analysis for water resource planning and management. *Water Resour. Manage.* **21**, 1553–1566. doi:10.1007/s11269-006-9112-5.

Hassoun, M. H. 1995 *Fundamentals of Artificial Neural Networks.* MIT press, Cambridge, MA, USA.

Howard, A. F. 1991 A critical look at multiple criteria decision making techniques with reference to forestry applications. *Can. J. Forest. Res.* **21**, 1649–1659. doi:10.1139/x91-228.

Hwang, C. L. & Yoon, K. 1981 *Multiple Attribute Decision Making: Methods and Applications.* Springer, Berlin.

Li, X., Guo, S. L., Liu, P. & Chen, G. Y. 2010 Dynamic control of flood limited water level for reservoir operation by considering inflow uncertainty. *J. Hydrol.* **391**, 124–132. doi:10.1016/j.jhydrol.2010.07.011.

Lippmann, R. P. 1987 An introduction to computing with neural nets. *ASSP Magazine, IEEE* **4**, 4–22. doi:10.1109/MASSP.1987.1165576.

Luo, J. G., Chen, C. X. & Xie, J. C. 2015 Multi-objective immune algorithm with preference-based selection for reservoir flood control operation. *Water Resour. Manage.* **29**, 1447–1466. doi:10.1007/s11269-014-0886-6.

Malekmohammadi, B., Zahraie, B. & Kerachian, R. 2011 Ranking solutions of multi-objective reservoir operation optimization models using multi-criteria decision analysis. *Expert Syst. Appl.* **38**, 7851–7863. doi:10.1016/j.eswa.2010.12.119.

Morris, M. D. 1991 Factorial sampling plans for preliminary computational experiments. *Technometrics* **33**, 161–174.

Ouyang, S., Zhou, J. Z., Qin, H., Liao, X. & Wang, H. 2014 A novel multi-objective electromagnetism-like mechanism algorithm with applications in reservoir flood control operation. *Water Sci. Technol.* **69** (6), 1181–1190. doi:10.1016/j.eswa.2010.12.119.

Parasuraman, K., Elshorbagy, A. & Carey, S. K. 2006 Spiking modular neural networks: a neural network modeling approach for hydrological processes. *Water Resour. Res.* **42** (5). doi:10.1029/2005WR004317.

Paturel, J. E., Servat, E. & Vassiliadis, A. 1995 Sensitivity of conceptual rainfall-runoff algorithms to errors in input data-case of the GR2M model. *J. Hydrol.* **168**, 111–125. doi:10.1016/0022-1694(94)02654-T.

Qin, H., Zhou, J. Z., Lu, Y. L., Li, Y. H. & Zhang, Y. C. 2010 Multi-objective cultured differential evolution for generating optimal trade-offs in reservoir flood control operation. *Water Resour. Manage.* **24**, 2611–2632. doi:10.1007/s11269-009-9570-7.

Shi, J. J. 2000 Reducing prediction error by transforming input data for neural networks. *J. Comput. Civ. Eng.* **14** (2), 109–116. doi:10.1061/(ASCE)0887–3801(2000)14:2(109).

Sobol, I. M. 2001 Global sensitivity indices for nonlinear mathematical models and their Monte Carlo estimates. *Math. Comput. Simul.* **55**, 271–280. doi:10.1016/S0378-4754(00)00270-6.

Wang, X. J., Zhao, R. H. & Hao, Y. W. 2011 Flood control operations based on the theory of variable fuzzy sets. *Water Resour. Manage.* **25**, 777–792. doi:10.1007/s11269-010-9726-5.

Wang, H. C., Jiao, W. L., Lahdelma, R., Zhu, C. Z. & Zou, P. H. 2014 Stochastic multicriteria acceptability analysis for evaluation of combined heat and power units. *Energies* **8**, 59–78. doi:10.3390/en8010059.

Yu, Y. B., Wang, B. D., Wang, G. L. & Li, W. 2004 Multi-person multiobjective fuzzy decision-making model for reservoir flood control operation. *Water Resour. Manage.* **18**, 111–124.

Zhong, P. A., Zou, C. G., Li, W. & Zhang, C. W. 2003 Stage trial-and error method and its application to reservoir operation for flood control. *Adv. Sci. Tech. Water Resour.* **23**, 21–23, 56 (in Chinese).

Zhu, F. L., Zhong, P. A., Xu, B., Wu, Y. N. & Zhang, Y. 2016a A multi-criteria decision-making model dealing with correlation among criteria for reservoir flood control operation. *J. Hydroinform.* **18**, 531–543. doi:10.2166/hydro.2015.055.

Zhu, F. L., Zhong, P. A., Wu, Y. N., Sun, Y. M., Chen, J. & Jia, B. Y. 2016b SMAA-based stochastic multi-criteria decision making for reservoir flood control operation. *Stoch. Environ. Res. Risk. A.* doi:10.1007/s00477-016-1253-3 (in press).

First received 29 May 2016; accepted in revised form 30 January 2017. Available online 7 March 2017