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# Deriving Reservoir Refill Operating Rules by Using the Proposed DPNS Model

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**Abstract.** The dynamic programming neural-network simplex (DPNS) model, which is aimed at making some improvements to the dynamic programming neural-network (DPN) model, is proposed and used to derive refill operating rules in reservoir planning and management. The DPNS model consists of three stages. First, the training data set (reservoir optimal sequences of releases) is searched by using the dynamic programming (DP) model to solve the deterministic refill operation problem. Second, with the training data set obtained, the artificial neural network (ANN) model representing the operating rules is trained through back-propagation (BP) algorithm. These two stages construct the standard DPN model. The third stage of DPNS is proposed to refine the operating rules through simulation-based optimization. By choosing maximum the hydropower generation as objective function, a nonlinear programming technique, Simplex method, is used to refine the final output of the DPN model. Both the DPNS and DPN models are used to derive operating rules for the real time refill operation of the Three Gorges Reservoir (TGR) for the year of 2007. It is shown that the DPNS model can improve not only the probability of refill but also the mean hydropower generation when compare with that of the DPN model. It's recommended that the objective function of ANN approach for deriving refill operating rules should maximize the yield or minimize the loss, which can be computed from reservoir simulation during the refill period, rather than to fit the optimal data set as well as possible. And the derivation of optimal or near-optimal operating rules can be carried out effectively and efficiently using the proposed DPNS model.

**Key words:** artificial neural network, dynamic programming, operating rules, optimal operation, Three Gorges Reservoir

## 1. Introduction

Reservoirs are one of the most efficient measures for the integrated water resources development and management. By altering the spatial and temporal distribution of runoff, reservoirs serve for multi-purposes, such as flood control, hydropower generation, water supply, navigation and recreation, in which reduce human's dependence on the nature availability of water. With the rapid development of social economy and water requirement, the function of reservoir becomes more and more important nowadays in China (Guo *et al*., 2004).

Various reservoir operation models based on optimization and simulation method have been proposed and reviewed by many authors (Yeh, 1985; Simonovic, 1992; Wurbs, 1993; Guo, 2000; Guo *et al.*, 2004). From these works, optimization techniques have been discussed in detail to determine the best sequences of releases, as well as the simulation techniques have been suggested to verify and analyze the performance of reservoir under changing conditions. Recently, Labadie (2004) reviewed the optimal operation of the multi-reservoir systems, along with the application of new techniques, such as genetic algorithm (GA), artificial neural network (ANN) and fuzzy theory.

Because of its ability in global searching and independence of the particular problem, GA has been widely applied to a variety of problems in the reservoir planning and management (Oliveira and Loucks, 1997; Neelakantan and Pundarikanthan, 2000; Chang and Chang, 2001; Ponnambalam *et al.*, 2003), especially in the optimization of the operating rules curves of reservoirs (Chang and Chen, 1998; Chen, 2003; Koutsoyiannis and Economou, 2003). Chang and Chen (1998) compared the real-coded and binary-coded genetic algorithms for function optimization in the application of a flood control reservoir model. The results show that both genetic algorithms are more efficient and robust than the random search method, with the real-coded GA performing better in terms of efficiency and precision than the binary-coded GA. Based on a real-coded genetic algorithm (RGA), Chen (2003) derived long-term reservoir operation rules by using an optimization and simulation model and found that RGA can minimize the water deficit and maintain the high water level of the reservoir.

The operating rules, which are the relationships that series of optimal releases are generally expressed as a function of reservoir state variables and hydrological input such as storage, inflows, etc., can be found from deterministic optimization using a linear or nonlinear regression procedure (Young, 1967; Bhaskar and Whitlatch, 1980). This is a method of the implicit stochastic programming, where most stochastic aspects of the problem, including spatial and temporal corrections of unregulated inflows, are implicitly included and deterministic optimization and/or simulation methods can be directly applied based on the past or synthetic recorders. The implicit stochastic approach makes reservoir operation very simple in practice, and it can work very well in median or large reservoir in terms of the capacity relative to the mean annual flow (Karamouz and Houck, 1987). In general, the implicit stochastic approach is one of the most reliable reservoir modeling techniques today (Simonovic, 1987). However, the selection of the operating rules proved to be the most difficult problem to tackle in applying the implicit stochastic approach (Saad *et al.*, 1994).

Since the ANN approach is particularly valuable in performing classification and pattern recognition functions for processes governed by complex nonlinear interrelationships, it has been suggested and widely used to derive operating rules (Saad *et al.*, 1994; Chandramouli and Raman, 2001; Rao *et al.*, 2001; Cancelliere *et al.*, 2002, 2003; Chandramouli *et al.*, 2002). For example, Saad *et al.* (1994)

illustrated an application of a five reservoirs system by the way of the learning disaggregation technology, which the operating rules are obtained by using ANN model to learn from optimal sequences of contents. Some hybrid ANN models, such as neural-fuzzy system and the combinations of ANN and GA, has been applied to derive operating rules effectively (Chang and Chang, 2001; Naresh and Sharma, 2001; Hasebe and Nagayama, 2002; Ponnambalam *et al.*, 2003). It has been shown that the ANN model is very favorable for deriving operating rules and the best way representing the operating rules due to its ability of mapping complex nonlinear interrelationships. The ANN model was also adopted to improve the rapidity of optimization (Neelakantan and Pundarikanthan, 2000), and it has a particular feature in the applications of ANN model in reservoir operation.

Raman and Chandramouli (1996) proposed the dynamic programming neural-network (DPN) model for deriving operating rules. By comparing the DPN model with (explicit) stochastic dynamical programming, standard operating policy, and dynamic programming regression, it is found that the DPN model is superior to other three operation models. Similarly, Jain *et al.* (1999) compared the standard linear operation policy and three operating rules based on dynamic programming (DP), including DPN, linear regression and nonlinear regression. The results showed that the performance of DPN model is better than other models.

The DPN model is designed to fit the optimal or near-optimal sequences of releases (training data set) as well as possible, i.e., the DPN model is to minimize the error between outputs of ANN and the optimal sequences of releases generated by DP or other optimization techniques. However, the objective of deriving operating rules is to maximize yield or minimize loss. The maximum $R^2$ (the square of the correlation coefficient, a measure of goodness of fit) criterion for selecting operating rules may not always be appropriate and does not always produce the best operating rules as measured by simulation in actual operation (Bhaskar and Whitlatch, 1980). There are some errors in curve fitting that includes the ANN model, which is likely to mislead the operation tracks deviating from optimal sequences of releases in actual operation. Many authors have advocated the simulation-based optimization or combined optimization and simulation approach in deriving operating rules, and some refinements or modifications of operating rules were developed (Karamouz and Houck, 1982; Simonovic, 1987, 1992; Wurbs, 1993; Oliveira and Loucks, 1997; Neelakantan and Pundarikanthan, 2000; Koutsoyiannis and Economou, 2003).

This paper is aimed at making some improvements to the DPN model by the method of simulation-based optimization. A modified DPN model, named dynamic programming neural-network simplex (DPNS), is proposed and developed. Based on simulation, the DPNS model uses Simplex (Nelder and Mead, 1965) to refine or re-optimize the DPN model in order to maximize the hydropower generation. The DPNS model has been applied to derive the refill operating rules in the Three Gorges Reservoir (TGR) that is a vitally important and backbone project in the development and harnessing of the Yangtze River in China. The performance of

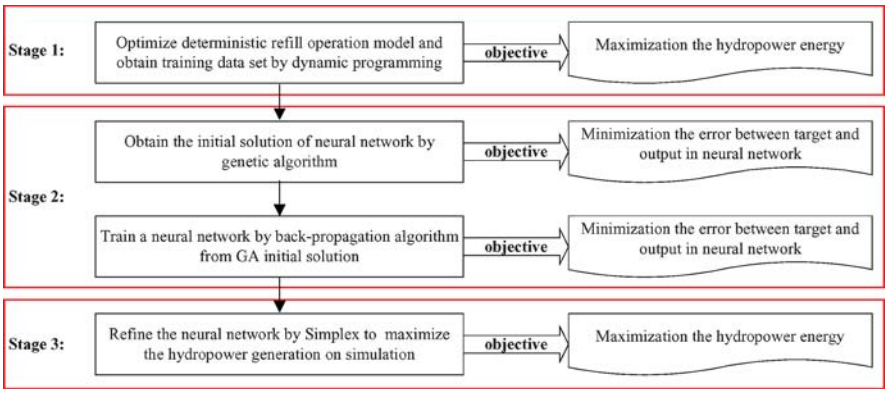



*Figure 1*. General framework of the DPNS model.

the DPNS model is also compared with that of the DPN model by the method of simulation techniques.

## 2. The Proposed DPNS Model

The proposed DPNS model is aimed at making some improvements to the DPN model and used to derive reservoir real time refill operating rules. The DPNS model consists of three stages as shown in Figure 1 and the first two stages are the same as the DPN model.

(1) By solving the deterministic mathematical model, the optimal or near-optimal sequences of releases (training data set) are generated through a classical optimization DP.
(2) The factors affecting the decision are selected as the input variables. At the same time, the decision variable, commonly is reservoir release or storage, is selected as the output variable. Then the relationship between input and output variables is mapped with ANN approach, which is trained by GA and back-propagation (BP) algorithm.
(3) By choosing maximum the hydropower generation as objective function, the Simplex method is used to refine the final output of the DPN model through simulation-based optimization.

### 2.1. RESERVOIR REFILL OPERATION BY USING DP

According to the Chinese Flood Control Act, the water level of reservoirs should below flood control level $Z_f$ as shown in Figure 2, in order to provide storage for flood protection during flood season. In the refill period, water should be refilled or impounded to normal pool level $Z_n$ for the purpose of normal water uses during the dry season, such as agricultural irrigation and municipal water supply. It is very

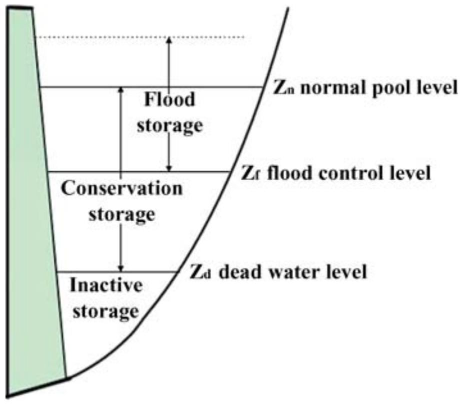



*Figure 2*. Reservoir storage zones and index levels.

important to determine an optimal reservoir operating rules for refilling water in refill period, with the aim to maximize the hydropower generation during the refill period under the condition that the reservoir is filled up.

During the refill period, reservoir water level should start from flood control level, and rises constantly till normal pool level before the starting of dry season. That is, the beginning and the final water levels are flood control level $Z_f$ and normal pool level $Z_n$ if the refill operation is feasible. Mentioned that filling the reservoir before the starting of dry season may also be treated as an operating rule for annual or monthly operation, and an explicit rule to satisfy the constraint (filling the reservoir by the end of refill period) strictly would be inappropriate from a point of global optimization in whole time (months or years), but this is used for simplifying the problem.

Assuming that there is not any flood risk during the refill period, the objective function of reservoir operation is to maximize the sum of hydropower generation, which can be described as

$$\text{maximize} \quad \sum_{t=1}^{n} E_t \tag{1}$$

$$\text{subject to} \quad S_{t+1} = S_t + I_t - R_t \quad t = 1, 2, \cdots, n-1 \tag{2}$$

$$N_{\min} \le N_t \le N_{\max} \tag{3}$$

$$R_{\min} \le R_t \le R_{\max} \tag{4}$$

$$S_{\min} \le S_t \le S_{\max} \tag{5}$$

where $t$: current time interval; $E_t$: hydropower generation during stage $t$; $S_t$: storage at the beginning of stage $t$; $I_t$: reservoir inflow during stage $t$; $R_t$: release from reservoir during stage $t$; $N_t$: power output during stage $t$; $N_{\min}$: firm output for reliability among power systems; $N_{\max}$: maximum output of hydropower generations; $R_{\min}$:

minimum release in reservoir for other purposes, such as environment or navigation; $R_{\max}$: maximum release in reservoir for the constraint of spill gates; $S_{\min}$: minimum storage permitted in reservoir that is the storage corresponding to the dead water level $Z_d$; $S_{\max}$: storage capacity of reservoir that is the storage corresponding to the normal pool level; $n$: total number of optimization stages.

Based on the reservoir rule curve, the initial and final water levels $Z_f$ and $Z_n$ can be predetermined in refill period. It is noted here that the losses of evaporation and leakage of reservoir are neglected in Equation (2) because they are very small in real time operation. Since reservoir refilling in every year is independent, this refill operation model can be established and optimized each year respectively.

The reservoir refill operation is the same as other deterministic reservoir operation problems, which can be solved within a classical DP framework. The discrete differential dynamic programming (DDDP) is implemented to solve Equations (1)–(5), within considering the following recursive equation

$$f_{t+1}(S_{t+1}) = \max[E_t + f_t(S_t)] \tag{6}$$

The DDDP is a modification of DP in order to speed the compute time and was well reviewed by Yeh (1985) and Labadie (2004). Since the DDDP needs a good initial policy (sequences of states) and can't guarantee finding the global optimum solution, many initial policies assumed are implemented and the sequences of releases associated with the maximum objective can be selected as the final solution. In principle, GA can be used to optimize the reservoir releases, but it may be very time consuming to find the global optimal solution.

## 2.2. TRAINING OF ANN BY USING GA AND BP

### 2.2.1. *Structure of ANN*

The optimal sequences of releases (training data set) are generated by optimization of the reservoir refill operation by solving Equations (1) to (6). The relationship between input (independent) variables, such as current storage and forecasted inflow, and the dependent (output) variable (current release or next storage) should be established. For the ability of approximating nonlinear relationship in a satisfactory way, the ANN model has been widely used to derive operating rules, which the inputs of ANN are the reservoir state variables and hydrological data (storage, inflows, etc.), and the outputs of ANN are optimal releases.

The structure of the ANN model both for operating rules and the real time reservoir simulation is shown in Figure 3. The current time, which is described as $i$th day, is selected as input of ANN and the operating rules in whole refill period can be depicted using only one ANN model (Chang and Chang, 2001). Several pre-storages (denoted as $k$) and different length of lead-time forecasted inflows (denoted as $t$) are chosen as inputs of ANN, and the values of $k$ and $t$ are selected

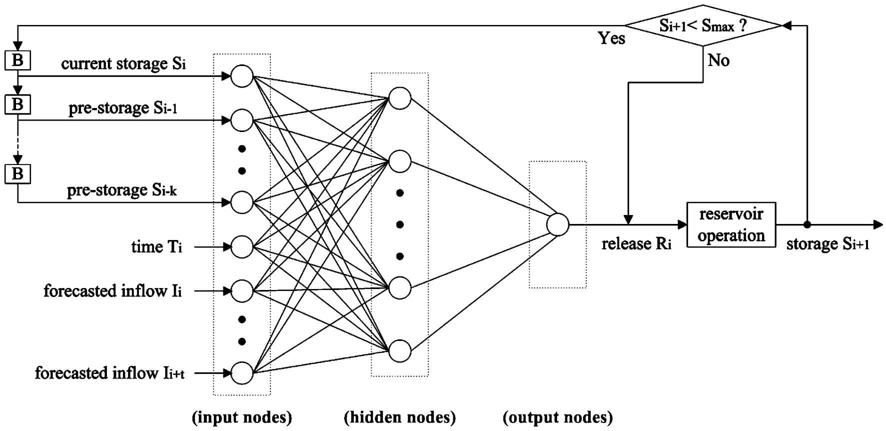



*Figure 3*. The structure of ANN model for reservoir refill operation (B denotes backward shift operator).

by the method of trial and error. It is well known that the precision of hydrological forecast is reduced as the increasing of lead-time. Only finite length of lead-time forecast can be used in practice. Since the reservoir flood forecasting and control system software has been widely applied in China, the length of lead-time and the precision of hydrological forecast have been greatly improved in past decades (Guo, 2000; Guo *et al.*, 2004).

2.2.2. *Training*

It's well known that the BP algorithm is a very effective and efficient method in ANN training based on gradient descent searching (Rumelhart *et al.*, 1986; Xiong *et al.*, 2004). The BP algorithm is so sensible to the initial solution due to gradient-based searching that advice has been given to generate the initial solution through GA rather than random method (Belew *et al.*, 1991; Skinnert and Broughton, 1995). GA is a heuristic technique for searching over the solution space of a given problem in an attempt to find the best solution or set of solutions, similar to Darwin's principle of evolution and was proposed by Holland (1975). Because of its character in ability of global searching and independent of the particular problem being analyzed, GA has been widely applied to a variety of problems. However, GA is very computer time consuming to find the global optimal solution in a large-scale problem. Based on the advantages and limitations of GA and ANN, they have been combined frequently in two major ways. The first one is GA has been used to search for the weights of the network, or to reduce the size of the training set by selecting the most relevant features; the other one is to use GA to design the structure of the network (Belew *et al.*, 1991; Skinnert and Broughton, 1995). In this paper, GA is adopted to obtain the initial solution for BP algorithm. To use the GA in ANN training, two points have to be taken into consideration:

(1) The objective function is set the same as the objective of BP network, i.e., minimize the mean square error (MSE) as following

$$\text{Minimize} \quad \text{MSE} = \frac{1}{L}\sum_{i=1}^{L}(T_i - O_i)^2 \tag{7}$$

where $T_i$ is the target value for the $i$th pattern, $O_i$ is the output of ANN for the $i$th pattern, $L$ is the total number of patterns.

(2) In order to map neural networks onto GA strings, every weights of the ANN are represented straightforward by the chromosomes in GA (Belew *et al.*, 1991; Skinnert and Broughton, 1995). The BP algorithm is implemented to train the ANN model effectively when the initial solution is searched through GA method.

### 2.3. REFINE THE OPERATING RULES BY USING SIMPLEX METHOD

Since it is aimed at minimizing the error between target and output in Equation (7), the DPN model may not perform well in terms of maximum hydropower generation in the actual operation, but gives a best fit to the optimal data set. Datta and Burges (1984) have addressed the importance of the loss and utility functions, which may affect reservoir yield significantly. The maximum $R^2$ criterion does not always produce the best operating rules as measured by simulation in actual operation (Bhaskar and Whitlatch, 1980). The DPN model is an indirect method for deriving optimal operating rules, and there are some errors when uses the ANN model for curve fitting. The errors are likely to mislead the operation tracks deviating from optimal sequences of releases, especially in a daily actual operation.

As an alternative way to the optimization, simulation techniques have been widely used to verify and refine the operating rules. Although the simulation model is not able to generate an optimal solution to a reservoir problem directly, it can detect an optimal or near-optimal solution after making numerous runs of a model with alternative decision polices (Simonovic, 1992). The simulation-based optimization or combined optimization and simulation approach have been used for deriving reservoir operating rules, as well as some refinements or modifications of operating rules have been developed (Karamouz and Houck, 1982; Simonovic, 1987, 1992; Wurbs, 1993; Oliveira and Loucks, 1997; Neelakantan and Pundarikanthan, 2000; Koutsoyiannis and Economou, 2003).

The simulation of reservoir real time operation as shown in the Figure 3 can be carried out according to following steps:

(1) The reservoir release $R_i$ is calculated by analysis of current information (time, forecasted inflow, current and pre-storages) with the operating rules that are depicted by ANN.

(2) The release $R_i$ is adjusted to satisfy the constraints in the refill operation model. For example, assume that the minimum release ($R_{\min}$) is 4500 m$^3$/s, if the

output of ANN model is 4200 m$^3$/s, it will be adjusted to 4500 m$^3$/s when consideration of $R_{\min}$. With the release adjusted, the current reservoir operation is accomplished using the water balance Equation (2).

(3) The simulation is carried out daily by daily from the starting to the end of refill period in each year.

With the network weights of the DPN model as initial solution, the objective function of the DPNS model is to maximize mean hydropower energy (MHE) per year computed from simulation, which can be described as following

$$\text{maximize} \quad \text{MHE} = \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{n} E_{i,j} \tag{8}$$

where $E_{i,j}$ is the hydropower energy in $j$th period of $i$th year, $m$ is the number of years being simulated. To treat with the constraints in reservoir refill operation, Equations (2)–(5) are implemented implicitly in simulation, and the final water level of reservoir (in the ending of refill period) is guaranteed lifting to the normal pool level by the method of penalty function. The objective function is adapted as following

$$\text{maximize} \quad \frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{n} E_{i,j} - C \times \max[0, k] \tag{9}$$

where $k$ is the number of years does not fill the reservoir, $C$ is the penalty coefficient and often gives a very big positive value. The solutions that do not fill the reservoir will be dropped automatically in the procedures of optimization. The objective function (Equation (8)) is actually the same as the objective of optimization of refill operation model (Equation (1)).

The Simplex method (Nelder and Mead, 1965) is a zero-order search method, which not require evaluation of the function gradient, and can be applied to minimization $n$-dimensional problems without constraints. It has been widely used in the field of hydrology and water resources management, such as the calibration of hydrological models parameters (Xiong and O'Connor, 2000; Xiong and Guo, 2004). In principle, the Simplex can be replaced by another nonlinear unconstrained multivariable search technique, such as Powell. Bernon *et al.* (2001) has found that the Simplex is a more accurate and robust algorithm than that of the Powell. Therefore the Simplex algorithm is selected and used to carry out the idea of DPNS model in this study.

Since the Simplex method is very sensible to the initial solution and generally converges to the local solution nearest to the initial solution. Clearly, it is vital important to select an appropriate initial solution for obtaining a satisfied result. In the third stages of the DPNS model, the Simplex method is used to re-optimize or refine the operating rules by starting from the final solution of the DPN model. In the implementation of Simplex to refine the DPN model, connectionists of ANN are straightforward mapped to the variables planned to optimize. For example, an ANN model with structure of 5-7-1 (input nodes, hidden nodes and output nodes) is transferred to an optimization problem with 50 (equal to $(5 + 1) \times 7 + (7 + 1) \times 1$) variables if the activation is the sigmoid function. Obviously, the curse of dimensionality would be inescapable when using the method of direct search techniques with random initial solution. The Simplex method can work very well to adjust the network because the initial solution is outputted from the DPN model, which may have already been a near-optimal solution or around near-optimal solution.

## 3. Case Study

### 3.1. THREE GORGES RESERVOIR

The Three Gorges Reservoir (TGR) is a vitally important project in the development and harnessing of the Yangtze River in China (Figure 4). The Yangtze River is one of the largest rivers in the world, which its upstream is intercepted by the TGR with length of main course about $4.5 \times 10^3$ km and drainage area of $1 \times 10^6$ km$^2$. With all the profiles being narrow and deep, the TGR will still keep the original river section's shape of long narrow belt and belong to a typical river channel type reservoir. The mean annual runoff at the dam site is $4.51 \times 10^{11}$ m$^3$.

The TGR is the largest multipurpose hydro-development project ever built in the world and its comprehensive benefits mainly include flood control, power generation and navigation improvement. The design reservoir storage at the normal pool level 156 m (the early stage) and 175 m (the normal stage) are $2.348 \times 10^{10}$ m$^3$

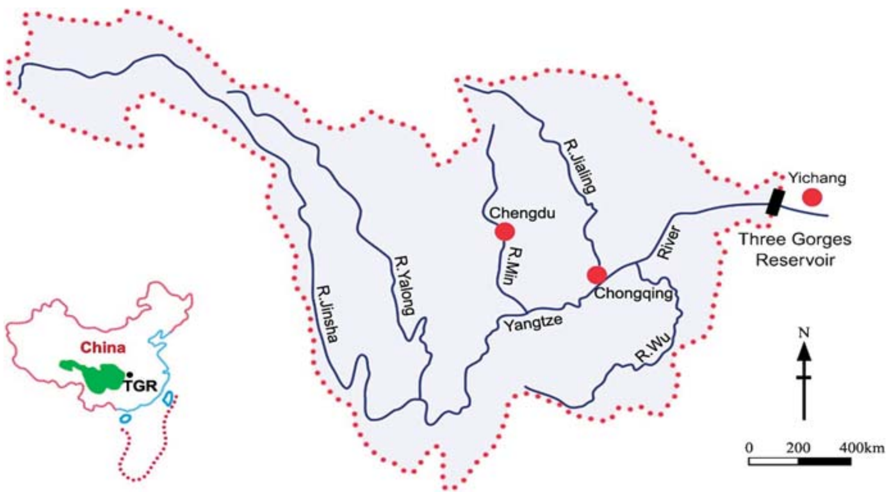



*Figure 4*. The location of Three Gorges Reservoir basin.

*Table I.* The operation parameters during early stage (2007–2009)

| Flood control level (m) | Normal level pool (m) | The initial storage ($\times 10^9$ m$^3$) | The final storage ($\times 10^9$ m$^3$) | Firm output/ $N_{\min}$ (MW) | Minimum release/ $R_{\min}$ (m$^3$/s) | Minimum storage/ $S_{\min}$ ($\times 10^9$ m$^3$) | Maximum storage/ $S_{\max}$ ($\times 10^9$ m$^3$) |
|---|---|---|---|---|---|---|---|
| 135 | 156 | 12.4 | 23.48 | 3600 | 4500 | 12.4 | 23.48 |

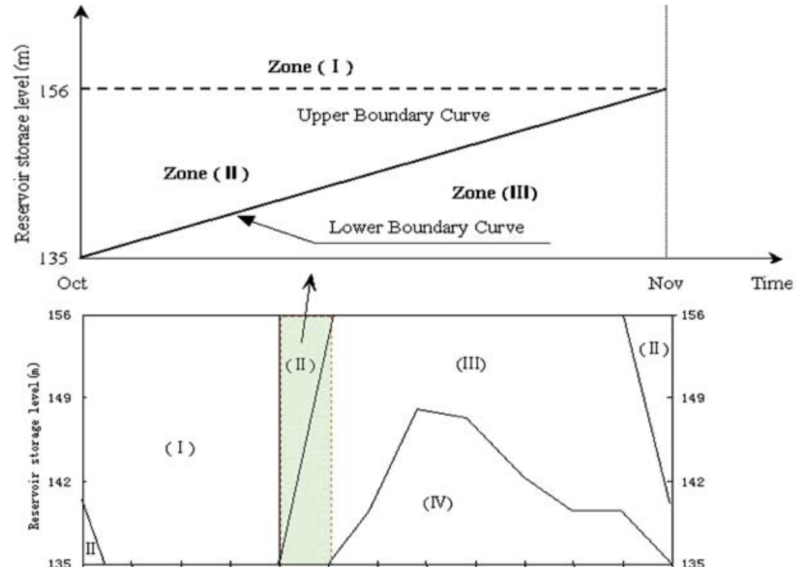
and $3.93 \times 10^{10}$ m$^3$, of which $1.108 \times 10^{10}$ m$^3$ and $2.215 \times 10^{10}$ m$^3$ will be flood protection storage, respectively. The project consists of three major parts, i.e., the large dam across the Yangtze River, the hydroelectric power station houses and the navigation structures. The dam is a concrete gravity type, with a crest elevation of 185 m above sea level, a dam axis length of 2,309 m, and the maximum height of 175 m. There are 14 and 12 sets of hydraulic turbo generators installed in the left and right powerhouses, respectively. Thus the 26 sets of hydraulic turbo generators, with 700 MW for each set, totaling $1.82 \times 10^7$ kW in installed capacity, will produce an annual electricity output of $8.47 \times 10^{10}$ kWh.

According to the schedule, the construction of the project started in 1993, and in 1997 the main river course were closed. In 2003, the first batch of generating units was put into operation and generated electricity; and by 2009 the whole TGR project will be completed. The refill operational parameters and constraints of TGR during 2007 to 2009 (the early stage) are listed in Table I. The operation of TGR for the year of 2007 (first year in the early stage) is selected as the case study.

According to the statistical properties of reservoir inflow in the refill period (October), the mean, minimum and maximum value are $51.64 \times 10^9$ m$^3$, $28.30 \times 10^9$ m$^3$ and $88.87 \times 10^9$ m$^3$ respectively. Extracting the discharge for firm output (about 5500 m$^3$/s), the TGR can reach the normal pool level by the end of October even in dry year. Therefore, maximizing the sum of hydropower generation was chosen as an objective function with the constraint that the normal pool level must be reached by the end of October. In September, the mean and minimum inflows are 26400 m$^3$/s and 13200 m$^3$/s, respectively. On the 30th September, the mean and minimum inflows are 24500 m$^3$/s and 9500 m$^3$/s respectively in the past 120-year. The inflows of the TGR are much greater than the discharge for firm output. Therefore it is impossible that the initial reservoir level at the beginning of October would be far below the flood control level due to the large inflow of the TGR.

## 3.2. DESIGNED OPERATING RULES OF TGR

In the early stage operation of TGR, the rule curve (Figure 5) has been planned to refill water in the refill period (October). According to scheme, the reservoir refill operation is guided by the upper and lower boundary curve. That is, water should be spilled to ensure the reservoir water level is below the normal pool level (156 m) when the reservoir water level of storage is on the top of upper boundary curve




| month | Jun | Jul | Aug | Sep | Oct | Nov | Dec | Jan | Feb | Mar | Apr | May |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Upperboundarycurve | 135 | 135 | 135 | 135 | 156 | 156 | 156 | 156 | 156 | 156 | 156 | 140 |
| Lowerboundarycurve | 135 | 135 | 135 | 135 | 135 | 140 | 148.2 | 147.4 | 142.1 | 140 | 140 | 135 |

*Figure 5*. The rule curve of TGR during early stage (2007–2009).

(zone I), and the power station generates the firm output when the reservoir water level is below the lower boundary curve (zone III), otherwise the generators are turned to maximize output if the water level is in zone II. The designed operating rules can be regarded as a standard operating policy (SOP).

Although the SOP is very easy to implement in practice, there's several limitations through simulation the rules with historical recorders. (1) The reservoir can't be refilled to the normal pool level in many years, especially in some dry years the water level in the end of refill period is far less than the normal pool level. (2) For the hydropower generation is increased at once when the water level is upon the lower boundary curve, the hydraulic head is so low that the waterpower isn't utilized sufficiently and the water usage is inefficient. It's very valuable in deriving an optimal operating rule for more reliability in filling (probability of refill) and more hydropower energy production. It should be noted that the storage capacity of TGR is very small compared with the mean annual flow at dam site, and it is not suitable for application of the implicit stochastic programming in annual operation (Karamouz and Houck, 1987).

### 3.3. COMPARISON OF THE RESULTS

The daily inflow data in October from 1882 to 2001, at the Yichang hydrological station that is located about 40 km downstream of the TGR, is used in this study.

The data set is partitioned into two, one for the training from 1882 to 1981, and another for validation or verification from 1982 to 2001. With the proposed refill operation model, DDDP is implemented to solve Equations (1)–(6) with the training and validation recorders respectively. For the optimal sequences of release may be not unique in this case (will be discussed below), the sequences of releases that filling reservoir as fast as possible in all the optimal sequences are selected as the training data and used for training or verifying the DPN and DPNS models. By analysis of the deterministic optimization results, the release usually is equal to the inflow when the reservoir is filled up. To reduce the interferences may be caused by them, these contents are subtracted from the training data set.

Zhang *et al.* (2005) has studied the hydrological forecasting precision of the TGR and the results are listed in the Table II. It is shown that the forecasting precision decreases as the lead-time increase. The Nash-Sutcliffe efficiency, the relative error of the volumetric fit and the mean relative error of the peak flow are 95.87, 3.00, and 8.10%, respectively for 3-day lead-time forecasting. Four operating rules (Table III), including two DPN and two DPNS models used the forecasted inflow of 1 day and 3 days lead-time respectively, are studied and evaluated. The number of pre-storages ($k$) is set to 3 and the number of hidden nodes of ANN model is determined by trial-and-error procedure (Raman and Chandramouli, 1996). It is noted here that the 1 or 3 means that one or three day(s) lead-time forecast information is used.

Three evaluation criterions are used to compare the performance of different models, i.e.,

*Table II.* Hydrological forecasting error in TGR

| | Discharge | | | Stage |
|---|---|---|---|---|
| Lead-time length | Nash-Sutcliffe efficiency (%) | Relative error of the volumetric fit (%) | Mean relative error of the peak flow (%) | Mean error (m) |
| 1 day | 98.11 | −0.85 | 4.30 | 0.09 |
| 2 days | 97.54 | 1.60 | 5.80 | 0.16 |
| 3 days | 95.87 | 3.00 | 8.10 | 0.26 |

*Table III.* Four schemes of operating rules

| Operating rules | Forecasted lead-time | Input variables | Structure of ANN | The method of deriving operating rules |
|---|---|---|---|---|
| DPN1 | 1 day | $S_{i-3}, S_{i-2}, S_{i-1}, I_i, T_i$ | 5-7-1 | DPN |
| DPNS1 | 1 day | $S_{i-3}, S_{i-2}, S_{i-1}, I_i, T_i$ | 5-7-1 | DPNS |
| DPN3 | 3 days | $S_{i-3}, S_{i-2}, S_{i-1}, I_i, I_{i+1}, I_{i+2}, T_i$ | 7-8-1 | DPN |
| DPNS3 | 3 days | $S_{i-3}, S_{i-2}, S_{i-1}, I_i, I_{i+1}, I_{i+2}, T_i$ | 7-8-1 | DPNS |

(1) The mean hydropower energy (MHE) in simulation years, which is described as Equation (8).
(2) The probability of refill (PR) by the end of October is defined as.

$$\mathrm{PR} = \frac{k}{m} \times 100\% \tag{10}$$

In which means in $k$ out of $m$ years refilling reach to the normal pool level. According to the definition of the probability of refill, the operating rules would be perfect when PR is equal to 100%.
(3) The mean relative error (MRE) of the neural network model.

$$\mathrm{MRE} = \frac{1}{L}\sum_{i=1}^{L}\frac{|T_i - O_i|}{T_i} \times 100\% \tag{11}$$

In which $T_i$ is the target value for the $i$th pattern, $O_i$ is the output of ANN for the $i$th pattern, $L$ is the total number of patterns. It should be pointed out that the MRE is not consistent with the MSE in Equation (7) absolutely, but they are good measures for indicating the goodness of fit (Raman and Chandramouli, 1996). The MRE is used in the evaluation because it is a zero dimension term and able to give us information more visually. Among the above three evaluation criterions, only PR and MHE are valuable in assessment of the reservoir operation performance, and the MRE is a criterion to assess the goodness of fit in ANN model.

The performance of six models, including SOP, DP, DPN1, DPN3, DPNS1 and DPNS3, are compared and the results are listed in Table IV. The DP is an operation based upon the perfect known of inflow in the whole refill period and can be seen as an ideal operation in theory.

It can be inferred from that the SOP model is more conservative than the DPN and DPNS models in terms of the value of PR. Though SOP can generate more hydropower than DPN1 and DPN3 in the training period, the reservoir functions

*Table IV.* Comparison of operating rules in the refill operating for the year of 2007

| | Training | | | Validation | | |
|---|---|---|---|---|---|---|
| Operating rules | PR (%) | MHE ($\times 10^9$ kWh) | MRE (%) | PR (%) | MHE ($\times 10^9$ kWh) | MRE (%) |
| SOP | 93 | 7.5267 | / | 85 | 6.9025 | / |
| DP | 100 | 7.9157 | / | 100 | 7.5059 | / |
| DPN1 | 99 | 7.4463 | 5.53 | 100 | 7.0550 | 4.99 |
| DPNS1 | 100 | 7.6158 | 18.63 | 100 | 7.1814 | 19.88 |
| DPN3 | 100 | 7.4755 | 5.20 | 100 | 7.0514 | 4.85 |
| DPNS3 | 100 | 7.7236 | 15.00 | 100 | 7.2695 | 15.68 |

such as navigation and hydropower generation after October may be greatly affected since it dose not reach the normal pool level. The SOP procedure has consumed more quantity of water for littler energy. All of the DPN and DPNS models are superior to SOP in the validation period and are effectiveness for deriving the refill operating rules in general.

The performance of the DPNS is compared with the DPN model and the results are listed in Table IV. It is shown that the MHE could be increased by 2.28 (3.32) and 1.79% (3.09%) in training and validation periods, respectively. Obviously, the DPNS models can improve not only the probability of refill but also the mean hydropower generation and perform better than that of the DPN models.

Even though the MRE is insensible to the lengths of lead-time in forecasted inflow, the PR and MHE are actually related to the forecasted information. It is shown that the longer lead-time is, the more yield gives. In other words, the model performance is improved with increasing lengths of lead-time when the hydrological forecasting is reliable.

The hydropower generation of five operating rules during the validation period is plotted in Figure 6. Table IV and Figure 6 shows that the hydropower generation of DPNS models are more than that of SOP and DPN models in validation period and the reservoir is not all filled up by the end of refill period when using the SOP model. It is shown that the MHE of the DPNS3 model is increased by 2.62 and 5.32% in training and validation period respectively, and the PR of the DPNS model is reached 100%, as comparing to that of SOP. The DPNS3 model has the best performance under the condition of filling up the reservoir.

The 120-year October inflow series was ranked in descending order and plotted in the empirical frequency curve. As the October inflow volumes of 1949, 1992, and 1959 are approximately corresponding to the 20, 50, and 80% percentiles on the empirical frequency curve, the years of 1949, 1992 and 1959 are chosen to represent the wet, normal and dry years. These representative years have been used to compare the performance of DPNS model with those of DPN and SOP models, and the results are shown in Table V and Figures 7–9. Since the reservoir is all filled

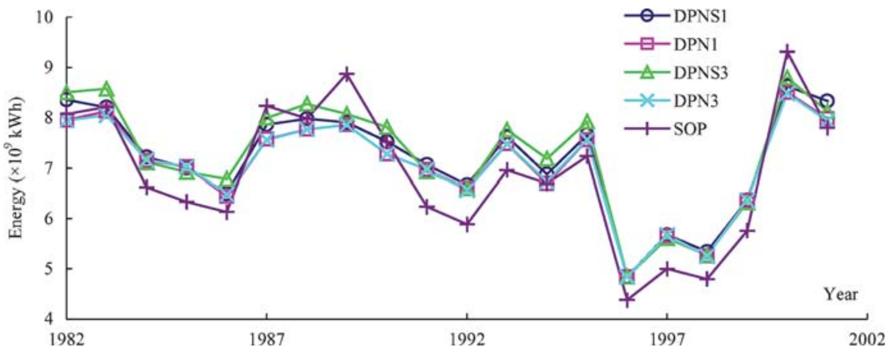



*Figure 6*. Comparing the hydropower generation in validation period.

*Table V.* Comparison of three operating rules in representative year

| Representative year | Hydropower generation ($\times 10^9$ kWh) and increase compared to SOP | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | SOP | DPN1 | | DPNS1 | | DPN3 | | DPNS3 | |
| 1949 (wet) | 8.4213 | 8.4298 | 0.10% | 9.1719 | 8.91% | 8.9317 | 6.06% | 9.3257 | 10.74% |
| 1992 (normal) | 5.8881 | 6.5680 | 11.55% | 6.5996 | 12.08% | 6.5971 | 12.04% | 6.6641 | 13.18% |
| 1959 (dry) | 3.9524 | 4.2769 | 8.21% | 4.3001 | 8.80% | 4.2896 | 8.53% | 4.3007 | 8.81% |

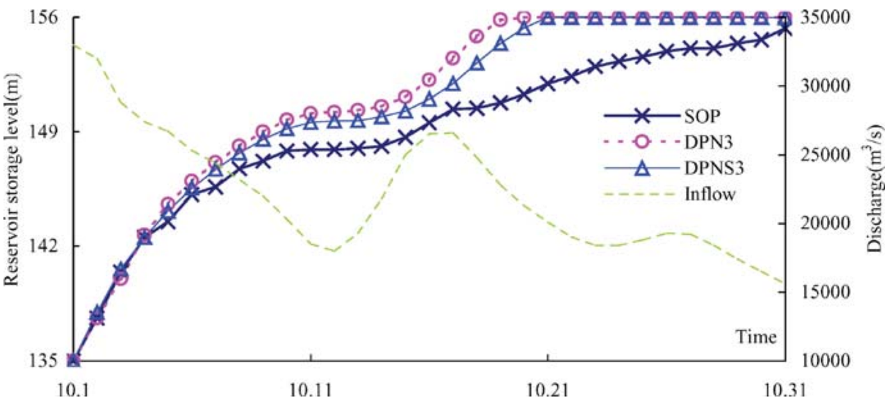



*Figure 7.* Refill tracks of three operating rules in wet year (1949).

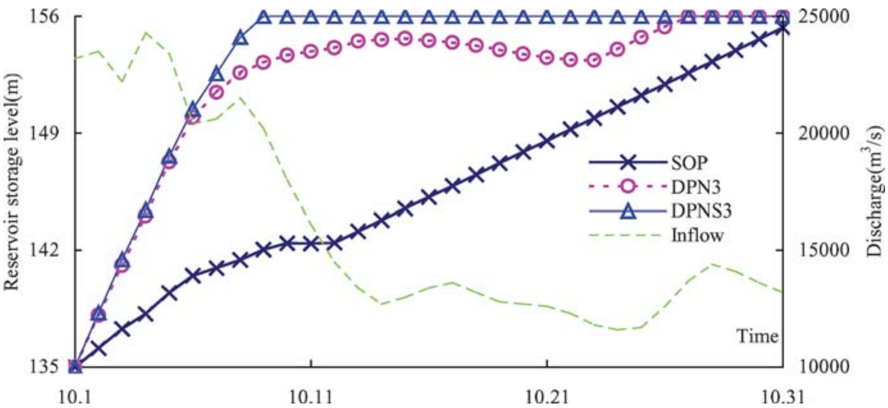



*Figure 8.* Refill tracks of three operating rules in normal year (1992).

up by the end of refill period in these years, the comparison can be only made in terms of hydropower energy. As compared with the SOP, the hydropower generated by DPNS3 increases 10.74, 13.18 and 8.81% respectively for the wet, normal and dry representative year. And as compared with the DPN1 (DPN3) model, the DPNS1 (DPNS3) model can increase the hydropower generation 8.80 (4.41), 0.48 (1.02),

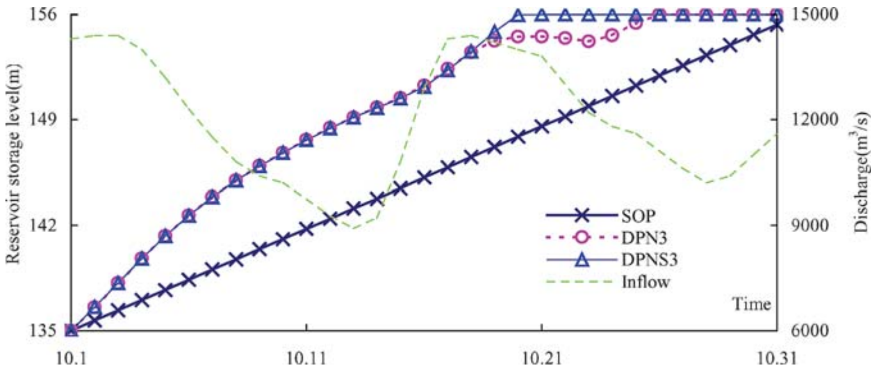



*Figure 9*. Refill tracks of three operating rules in dry year (1959).

0.54% (0.26%) respectively. It is also shown that the DPNS models are very robust in all kinds of years. The DPNS model can yield better than the DPN model, because of two reasons: (1) In the DPN model the error is unavoidable in the fitting to the optimal releases. Some errors between target and output of operating rules are insensitive and even have nothing to do with performance in reality because of some constraints in the practical operation. And the dependence of operation between adjacent periods, such as previous-current, or current-after, distorts the optimal sequence of release when there is only a tiny bias in previous operation. The DPNS model has not only planned to fit for the optimal sequences of releases but also taken into account the importance and transition of error, thus making it perform better than the DPN model. (2) The optimal sequences of releases may be not unique in this case. For example, two optimal tracks are shown in Figure 10 by optimizing the data of 2000, indicating there are not one sequences but a zone can reach optimal operation in reality. Hydropower generator has a maximal limit output ($N_{\max}$) in which does not generate more hydropower output no matter how to increase the hydraulic head or discharge. In the refill season, because water must be

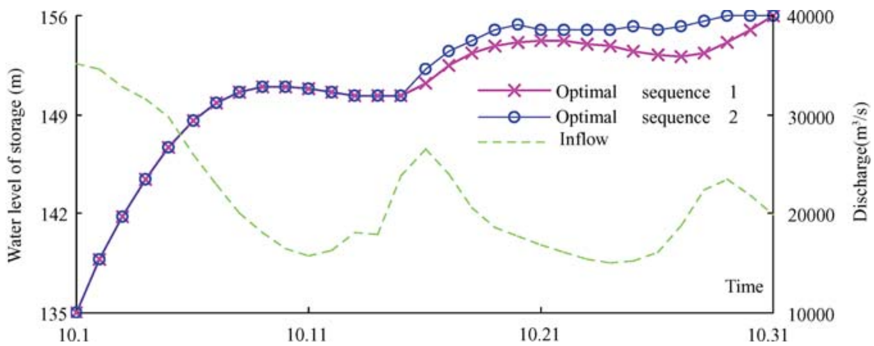



*Figure 10*. Two optimal operation sequences during refill period of 2000.

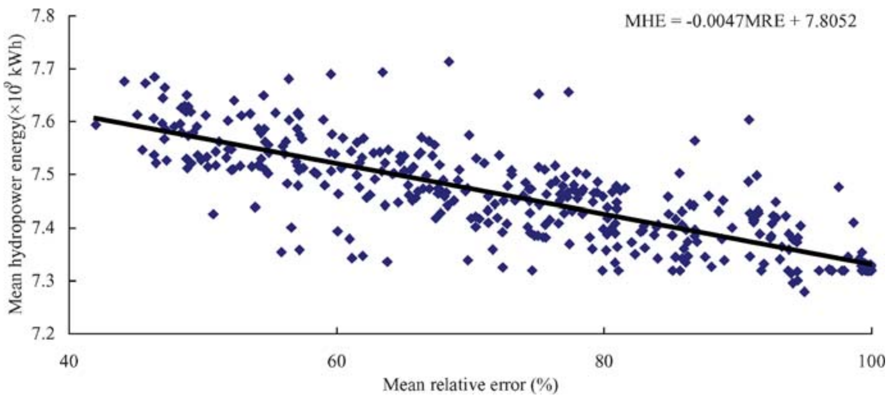



*Figure 11.* Relationship between MRE and MHE by using the Monte Carlo experiments.

spilled due to the reservoir storage capacity in the wet year, it isn't help to generate more energy in the way of improvement of the hydraulic head.

In order to analyze the relationship between goodness of fit and performance in operation further, a Monte Carlo (MC) experiment is implemented with following steps.

(1) The weights of ANN model are generated in random method and the corresponding operating rules are established.
(2) With simulation the recorder data, MHE, PR and MRE are computed using Equations (8), (10) and (11) respectively. The performance of ANN model established is compared based on evaluation criterions.

The MC experiments are implemented with the structure of 7-8-1 and data of 1882 to 1981, the results are shown in Figure 11. Some operating rules, which PR is not reach 100%, have been neglected so that the comparisons are uniform. Namely, since all points in the figure can refill reservoir in probability of 100%, only MRE and MHE have to be compared. It is shown that smaller MRE does not always mean more hydropower energy. By statistical analysis, the correlation coefficient between MRE and MHE is $-0.814$, which the critical value at the 5% significance level is 0.099 (392 points total).

## 4. Conclusions

The dynamic programming neural-network simplex (DPNS) model, which is a modification of the dynamic programming neural-network (DPN) model, are proposed and applied to derive refill-operating rules in the Three Gorges Reservoir. The following conclusions are made:

(1) In the application of ANN model for deriving reservoir operating rules, it is ought to maximize the hydropower energy in the actual operation, rather than to

fit the optimal data set as well as possible. That is, the minimum MRE criterion does not always produce the best operating rules as measured by simulation and the goodness of fit is not direct related to the hydropower energy produced.
(2) The DPNS model can improve not only the probability of refill but also the mean hydropower generation when compare with that of the DPN and SOP models. The DPNS model is superior to the DPN model and is an effective and efficient method to derive operating rules.
(3) The DPNS3 model, which uses the maximum information of hydrological forecasting available, can produce the maximum hydropower energy under the condition of filling up the reservoir. It is suggested to use the DPNS3 model in TGR refill operation practice.

The DPNS model has been proposed to derive the refill rules for TGR in this study. In a similar way, DPNS can also be implemented in the annual reservoir operation to derive the optimal or near-optimal operating rules.

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## References

Belew, R., McInerney, J., and Schraudolph, N., 1991, 'Evolving networks: Using the genetic algorithm with connectionist learning', in Langton, C., Taylor, C., Farmer, C., and Rasmussen, S. (eds.), *Artificial Life II*, Redwood City, CA. Addison-Wesley, 511–547.

Bernon, J. L., Boudousq, V., Rohmer, J. F., Fourcade, M., Zanca, M., Rossi, M., and Mariano-Goulart, D., 2001, 'A comparative study of Powell's and Downhill Simplex algorithms for a fast multimodal surface matching in brain imaging', *Comput. Med. Imaging Graph.* **25**(4), 287–297.

Bhaskar, N. and Whitlatch, E., 1980, 'Derivation of monthly reservoir release policies', *Water Resour. Res.* **16**(6), 987–993.

Cancelliere, A., Giuliano, G., Ancarani, A., and Rossi, G., 2002, 'A neural networks approach for deriving irrigation reservoir operating rules', *Water Resour. Manage.* **16**(1), 71–88.

Cancelliere, A., Giuliano, G., Nicolosi, V., and Rossi, G., 2003, 'Optimal short-term operation of a multipurpose reservoir system under limited water supply', in Bloschl, G., Franks, S., Kumagai, M., Musiake, K., and Rosbjerg, D. (eds.), *Water Resources Systems-Hydrological Risk, Management and Development*, IAHS Publication, (281), 200–207.

Chandramouli, V. and Raman, H., 2001, 'Multireservoir modeling with dynamic programming and neural networks', *J. Water Resour. Plan. Manage.* **127**(2), 89–98.

Chandramouli, V., Kuppusamy, K., and Manikandan, K., 2002, 'Study on water sharing in a multi-reservoir system using a dynamic programming-neural network model', *Int. J. Water Resour. Dev.* **18**(3), 425–438.

Chang, F. and Chen, L., 1998, 'Real-coded genetic algorithm for rule-based flood control reservoir management', *Water Resour. Manage.* **12**(3), 185–198.

Chang, L. and Chang, F., 2001, 'Intelligent control for modelling of real-time reservoir operation', *Hydrol. Processes* **15**(9), 1621–1634.

Chen, L., 2003, 'Real coded genetic algorithm optimization of long term reservoir operation', *J. Am. Water Resour. Assoc.* **39**(5), 1157–1165.

Datta, B. and Burges, S., 1984, 'Short-term, single, multiple-purpose reservoir operation: Importance of loss functions and forecast errors', *Water Resour. Res.* **20**(9), 1167–1176.

Guo, S., 2000, *Reservoir Comprehensive and Automatic Control Systems*, Wuhan University of Hydraulic and Electric Engineering Press, Wuhan, China, (In Chinese).

Guo, S., Zhang, H., Chen, H., Peng, D., Liu, P., and Pang, B., 2004, 'Reservoir flood forecasting and control system in China', *Hydrol. Sci. J.* **49**(6), 959–972.

Hasebe, M. and Nagayama, Y., 2002, 'Reservoir operation using the fuzzy and neural network and fuzzy systems for dam control and operation support', *Adv. Eng. Software* **33**(5), 245–260.

Holland, J., 1975, *Adaptation in Natural and Artificial Systems*, University of Michigan Press, Ann Arbor.

Jain, S., Das, A., and Srivastava, D., 1999, 'Application of ANN for reservoir inflow prediction and operation', *J. Water Resour. Plan. Manage.* **125**(5), 263–271.

Karamouz, M. and Houck, M., 1982, 'Annual and monthly reservoir operating rules generated by deterministic optimization', *Water Resour. Res.* **18**(5), 1337–1344.

Karamouz, M. and Houck, H., 1987, 'Comparison of stochastic and deterministic dynamic programming for reservoir operating rule generation', *Water Resour. Bull.* **23**(1), 1–9.

Koutsoyiannis, D. and Economou, A., 2003, 'Evaluation of the parameterization-simulation-optimization approach for the control of reservoir systems', *Water Resour. Res.* **39**(6), 1170, doi: 10.1029/2003WR002148.

Labadie, J., 2004, 'Optimal operation of multireservoir systems: State-of-the-art review', *J. Water Resour. Plan. Manage.* **130**(2), 93–111.

Naresh, R. and Sharma, J., 2001, 'Reservoir operation using a fuzzy and neural system for hydrogeneration scheduling', *Int. J. Syst. Sci.* **32**(4), 479–486.

Neelakantan, T. and Pundarikanthan, N., 2000, 'Neural network-based simulation-optimization model for reservoir operation', *J. Water Resour. Plan. Manage.* **126**(2), 57–64.

Nelder, J. and Mead, R., 1965, 'A simplex method for function minimization', *Comput. J.* **7**(4), 308–313.

Oliveira, R. and Loucks, D., 1997, 'Operating rules for multireservoir systems', *Water Resour. Res.* **33**(4), 839–852.

Ponnambalam, K., Karray, F., and Mousavi, F., 2003, 'Minimizing variance of reservoir systems operations benefits using soft computing tools', *Fuzzy Sets Syst.* **139**(2), 451–461.

Rao, Z., O'Connell, P. E., Cook, D. J., and Jamieson, D. G., 2001, 'Deriving robust operating rules for the interim control of the Kirazdere reservoir', *Water Sci. Technol.* **43**(5), 277–284.

Raman, H. and Chandramouli, V., 1996, 'Deriving a general operating policy for reservoirs using neural network', *J. Water Resour. Plan. Manage.* **122**(5), 342–347.

Rumelhart, D., Hinton, G., and Williams, R., 1986, 'Learning representations by back-propagating errors', *Nature* **323**(9), 533–536.

Saad, M., Turgeon, A., Bigras, P., and Duquette, R., 1994, 'Learning disaggregation technique for the operation of long-term hydroelectric power systems', *Water Resour. Res.* **30**(11), 3195–3202.

Simonovic, S., 1987, 'The implicit stochastic model for reservoir yield optimization', *Water Resour. Res.* **23**(12), 2159–2165.

Simonovic, S., 1992, 'Reservoir systems analysis: Closing gap between theory and practice', *J. Water Resour. Plan. Manage.* **118**(3), 262–280.

Skinnert, A. and Broughton, J., 1995, 'Neural networks in computational materials science: Training algorithms', *Modelling Simul. Mater. Sci. Eng.* **3**(3), 371–390.

Wurbs, R., 1993, 'Reservoir-system simulation and optimization models', *J. Water Resour. Plan. Manage.* **119**(4), 445–472.

Xiong, L. and O'Connor, K. M., 2000, 'Analysis of the response surface of the objective function by the optimum parameter curve: How good can the optimum parameter values be?' *J. Hydrol*. **234**, 187–207.

Xiong, L., O'Connor, K., and Guo, S., 2004, 'Comparison of three updating schemes using artificial neural network in flow forecasting', *Hydrol. Earth Syst. Sci*. **8**(2), 247–255.

Xiong, L. and Guo, S., 2004, 'Effects of the catchment runoff coefficient on the performance of TOPMODEL in rainfall-runoff modeling hydrological processes', *Hydrol. Processes* **18**(10), 1823–1836.

Yeh, W., 1985, 'Reservoir management and operations models: A state-of-the-art review', *Water Resour. Res*. **21**(12), 1797–1818.

Young, G., 1967, 'Finding reservoir operating rules', *J. Hydraulics Div.* **93**(6), 297–321.

Zhang, H., Guo, S., Zhou, F., Liu, P., Cheng, H., Chen, G., Min, Y., and Yang, W., 2005, 'Flood forecasting model for Three Gorges Reservoir intervening basin by considering the precipitation prediction', *Journal of Yangtze River Scientific Research Institute*, **22**(1), 9–12 (In Chinese).