Application of a Novel Artificial Neural Network Model in Flood Forecasting

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Research Article

Keywords: Flood forecasting, artificial neural network, multi-hidden layer, topology of ANN, API model, distributed rainfall

Posted Date: August 30th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-796633/v1>

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Version of Record: A version of this preprint was published at Environmental Monitoring and Assessment on January 25th, 2022. See the published version at <https://doi.org/10.1007/s10661-022-09752-9>.

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21 **Abstract**

22 In this paper, a novel ANN flood forecasting model is proposed. The ANN model is
23 combined with traditional hydrological concepts and methods, takes the initial
24 Antecedent Precipitation Index (*API*), rainfall, upstream inflow and initial flow at the

forecast river section as input of model. The distributed rainfall is realized as the input of the model. The simulation is processed by dividing the watershed into several rainfall-runoff processing units. Two hidden layers are used in the ANN, and the topology of ANN is optimized by connecting the hidden layer neurons only with the input which has physical conceptual causes. Topological structure of the proposed ANN model and its information transmission process are more consistent with the physical conception of rainfall-runoff, and the weight parameters of the model are reduced. The arithmetic moving-average algorithm is added to the output of the model to simulate the pondage action of the watershed. Satisfactory results have been achieved in the upstream of Second Songhua river in Songhua basin from the Baishan reservoir to Fengman reservoir sections, and the Mozitan and Xianghongdian reservoirs in the upper reaches of Pi river in Huaihe Basin in China.

Key words Flood forecasting, artificial neural network, multi-hidden layer, topology of ANN, API model, distributed rainfall

1. Introduction

Accurate flood forecasting is important for flood control and disaster reduction and prevention. Therefore, various hydrological models for flood forecasting have been developed in history. These models can be classified into three major types: empirical statistical model, lumped conceptual hydrological model and distributed hydrological model. However, difficulties in the long-term practice of flood forecasting exist due to the complexity of rainfall-runoff process in a watershed. The heterogeneity of spatial distribution of rainfall always has been an important factor affecting the accuracy of flood forecasting. While it is difficult to solve these problems using the empirical statistical model and lumped conceptual hydrological model, since these models usually take the forecast basin as a whole unit and use the area average rainfall as the model input. The distributed hydrological model could solve the problems, but this kind

of model is complex in structure, complicated in calculation, and requires different types of data (Yu, 2008).

Artificial neural network (ANN) is a kind of machine learning technique, and has been widely used in the field of hydrology since 1990s (French et al., 1992; Kang et al., 1993; Hjelmfelt and Wang, 1993; Zhu et al., 1994; Hsu et al., 1995; Minns and Hall, 1996; Shamseldin A, 1997). The ANN has several mathematical structures, which are able to model highly complicated physical systems (Fotovatikhah et al., 2018), and are more flexible and also a less presumption-dependent method for hydrological systems (Sudheer and Jain, 2004). Artificial neural network techniques are useful for time series modelling and forecasting because they do not require detailed a priori knowledge of the underlying processes (Bruen and Yang, 2005). It has been applied for both rainfall-runoff modelling (Zhang and Govindaraju, 2000; Chidthong et al., 2009; C.L. Wu and K.W. Chau, 2011), and stream-flow forecasting (Zealand et al., 1999; Cigizoglu, 2003, 2005; Tayfur et al, 2007; Yaseena et al., 2019).

The ANN models currently applied in hydrological forecasting is basically the lumped models. In order to solve the complex characteristics of rainfall-runoff process, efforts have been made in many research to use ANN model combinations to establish forecasting models. Zhang and Govindaraju (2000) used a set of parallel ANN models to deal with rainfall-runoff simulation of different magnitude (low, medium, and high magnitudes). According to the different influencing factors and laws of runoff process, such as flood, recession and base flow, Jain and Srinivasulu (2006) used several parallel ANN models to simulate different parts (segments) of runoff hydrograph, i.e., baseflow, rising limb and falling limb, etc.

In many modelling applications, some traditional hydrological concepts and methods are also integrated into the ANN models to reflect the physical process of rainfall-runoff, Hjelmfelt and Wang (1993) showed that an ANN can be constructed to replicate the unit hydrograph. Jain and Srinivasulu (2006) demonstrated that the infiltration and the effective rainfall could be computed by simply subtracting the

incremental infiltration from the total rainfall for ANN modelling. Corzo and Solomatine (2007) used baseflow separation techniques for ANN modelling in flood forecasting.

Most of ANN models used for hydrological forecasting are of the classical Multi-Layer Perceptron (MLP) type. Some other type of ANN models have also been used in hydrological forecasting, such as, the extreme learning machine (Yaseena et al., 2019) and Support Vector Machine and Artificial Neural Network (Bafitlhile and Li, 2019)

Since ANN models have the ability to simulate highly complicated physical systems and are more flexible in structure while do not require more different types of data, we try to use ANN model to solve problems of the heterogeneity of spatial distribution of rainfall in flood forecasting. The ANN model is combined with traditional hydrological concepts and methods, and the key factors affecting runoff formation are taken as model inputs according to the physical process of rainfall-runoff. By optimizing the topology of ANN, distributed rainfall is realized as the input of the model. A flood forecasting ANN model is thus developed, which requires not much data, easy to use in real-time flood forecasting, and is expected to have good accuracy in flood forecasting.

2. Methodology

2.1. Introduction of Multi-Layer Perceptron

The proposed ANN model in this paper is based on the Multi-Layer Perceptron (MLP) type ANN model.

The MLP ANN. Such type of ANN generally consists of several layers. Each layer is composed of several parallel neurons. The information is transmitted gradually from the input layer to the output layer through the hidden layer. Each neuron processes received the information from every neuron in the back layer, and outputs the

information to every neuron in the front layer. Neuron is the information processing unit in the network. Each input of neuron has a parameter weight, and each input multiplies its weight and sums up to get the total value of the input information. When the total input value exceeds the threshold value, the neuron is activated to produce an output. The input information is thus converted to output through an activation function. The formula can be expressed as

$$o = f\left(\sum_{i=0}^n w_i x_i\right) \quad (1)$$

Where o is the neuron output, n is the number of neuron inputs, w_i is the weight of input, x_i is the neuron input, w_0 is the threshold value where $x_0 = -1$, $f(x)$ is the activation function.

The most commonly used activation functions are sigmoid function, linear function and hyperbolic tangent function. Where,

The linear function is as follows,

$$f(x) = x \quad (2)$$

The sigmoid function is formulated as follows,

$$f(x) = \frac{1}{1 + e^{-x}} \quad (3)$$

For the sigmoid function and hyperbolic tangent function, their maximum value is 1 and the minimum value is 0. Therefore, it is necessary to convert the input and output samples of the network to the values of interval $[0,1]$, which is called normalization processing. A number of normalization methods are available in practice. The most commonly used method is the proportional compression that can be expressed as,

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (4)$$

Where x' is the normalized data, $x_{\max}$ is the maximum data, $x_{\min}$ is the minimum data.

The back-propagation (BP) algorithms is the widely used training method of MLP ANN (Rumelhart et al., 1986). It is a supervised learning process that adjusts the neuron weight according to the error feedback from the output layer.

2.2. Take the key influencing factors of runoff formation

The antecedent soil moisture and the rainfall process, the changes of antecedent baseflow of a watershed and the inflow process of upstream channel, are key factors affecting the rainfall-runoff process of watershed outlet. Conceptual hydrological models based on the physical concept of rainfall-runoff, e.g., the Xinanjiang model (Zhao Ren-Jun, 1992) and Sacramento model (Burnash, 1995), are still effective and commonly used models in operational rainfall-runoff forecasting. The inputs of these models mainly include the antecedent soil moisture, rainfall process, evaporation, baseflow of a watershed. Wu and Chau (2011) proposed the input of a ANN which is similar to that of a conceptual model. It can be formulated as follows:

$$\bar{Q}_{t+T} = f(Q_{t+1-l_1}, P_{t+1-l_2}, S_{t+1-l_3}) \quad (5)$$

Where $\bar{Q}_{t+T}$ stands for the forecast flow at time instance $t+T$, Q_{t+1-l_1} is the antecedent flow (up to $t+1-l_1$ time steps), P_{t+1-l_2} is the antecedent rainfall (up to $t+1-l_2$ time steps), S_{t+1-l_3} (up to $t+1-l_3$ time steps) represents any other factors contributing to the true flow $\bar{Q}_{t+T}$ such as evaporation or temperature, l_1 , l_2 and l_3 stand for the number of previous flow, rainfall and other factors respectively.

In this paper, S (in Eq. 5) is replaced by the parameter of soil tension moisture in conceptual model. The Antecedent Precipitation Index (*API*) of API model (Linsley et

al., 1975), the most simple and effective index, is used to calculate the parameter of soil tension moisture. The calculation formula of API in the hydrological forecasting is as follows:

$$API_{t+1}=K(API_t+P_t), \quad API_{t+1} \leq IM \quad (6)$$

Where API_{t+1} stands for the API at time instance $t+1$, API_t stands for the API at time instance t , P_t stands for the rainfall in time interval from t to $t+1$, K is a parameter with different values for the different months, IM is the maximum value of API .

The unit hydrograph method (Sherman, 1932) has been widely used in real-time flood forecasting for a long time. The basic concept of unit hydrograph is that a period of effective rainfall forms a flow process (Fig. 1). Where, τp is the period of time when the flood peak of unit hydrograph appears, i.e, the time from the start of rainfall to the emergence of flood peak at the basin outlet. Based on this theory, the flow at time t is converted by the convolution of effective rainfall before time t , where, the runoff generated by rainfall before time $t-\tau p$ has entered the stage of recession, and the runoff converted by rainfall after time $t-\tau p$ is at the stage of rising. Therefore, the rainfall process from $t-\tau p$ to t is selected as the rainfall input, and these rainfall inputs are converted into runoff in a watershed. Accordingly, API selects the value at time $t-\tau p$ as the commence of the rainfall-runoff calculation. While the runoff converted by rainfall before $t-\tau p$ is accounted in the flow recession or baseflow by $Q_{t-\tau p}$, as the input of the flow recession. The formula is,

$$QO_t = f((API_{t-\tau p}, P_{t-\tau p+\Delta t}, \dots P_t), Q_{t-\tau p}) \quad (7)$$

Where, QO_t stands for the forecast flow at time instance t , $API_{t-\tau p}$ is the API at time instance $t-\tau p$, Δt is the time step of forecasting, $P_{t-\tau p+\Delta t}$ and P_t are the precipitation at time step $[t-\tau p, t-\tau p+\Delta t]$ and $[t-\Delta t, t]$, $Q_{t-\tau p}$ is the flow at time instance $t-\tau p$.

The upstream flow input shall also be considered as an important factor for the river channel that requires forecasting. Similar to the rainfall-runoff process, there is a

peak time τq in the unit hydrograph, that is, the time from the upstream pulse inflow to the outlet peak flow of the basin. Since the speed of river flow routing is in general faster than that of the overland flow, that is $\tau q < \tau p$, then the inflow process of upstream section from the time $t - \tau p$ to time t can be chosen as the input for the purpose of computational convenience. It can be expressed as

$$QO_t = f((API_{t-\tau p}, P_{t-\tau p+\Delta t}, \dots P_t), (QU_{t-\tau p}, QU_{t-\tau p+\Delta t}, \dots QU_t), Q_{t-\tau p}) \quad (8)$$

Where, $QU_{t-\tau p}$, $QU_{t-\tau p+\Delta t}$ and QU_t are the inflow of upstream section at time instance $t - \tau p$, $t - \tau p + \Delta t$ and t .

2.3. The novel artificial neural network

Commonly, the MLP ANN has one hidden layer. Kia et al. (2012) developed a two hidden layers MLP model, the flood level is simulated with rainfall, slope, elevation, flow accumulation, soil, land use as input. In this paper, based on the concept of deep learning one more hidden layer is used to reflect the physical process of runoff generation and watershed concentration. The ANN is divided into four layers (See Fig. 2). Starting from the bottom to top, the first layer (l_1) is the input layer, the second layer (l_2) and third layers (l_3) are the hidden layers that simulate the rainfall-runoff generation and watershed concentration, and the fourth layer (l_4) collects all runoff to the catchment outlet. In addition, an arithmetic moving-average (MA) processing is applied in the front of the layer 4.

In the MLP ANN, each neuron receives the information from every neuron in its back layer. In this paper, to accommodate the large number of distributed rainfall input, the topological structure of ANN is optimized to reduce those unnecessary neuron connections without physical meaning, therefore the input weight parameters that require calibration are substantially reduced to achieve effective training of ANN with two hidden layers and many neurons. Distributed rainfall input is processed by dividing the watershed into several rainfall-runoff processing units. In each unit area, the

rainfall-runoff process is only affected by the soil moisture and rainfall within the unit, it is not affected by the upstream flow, the soil moisture and rainfall from other units. Similarly, the calculation of upstream flow routing is not affected by the rainfall and other factors within the units. Based on the concept of deep learning Convolutional Neural Network (Krizhevsky et al., 2012) feature map, the 1-3 layers of the artificial neural network are divided into several groups as shown in Fig. 2. From the Fig. 2, the groups on the left side simulate the rainfall-runoff generation and flow concentration within the area of each rainfall-runoff processing unit. Groups on the right side simulate the flow routing of upstream river and the recession of baseflow from left to right respectively. Differ from the feature map, the neurons in these groups are only connected to the neurons in the front layer of the same groups respectively.

Regarding the group of rainfall-runoff simulation. In the first (input) layer, neurons from the left to right in Fig. 2 are the initial soil moisture ($API_{t-\tau p}$) at the time ($t-\tau p$) when the rainfall-runoff process commence in the rainfall-runoff processing unit, and the number of $\frac{\tau p}{\Delta t}$ rainfalls ($P_{t-\tau p+\Delta t}, P_{t-\tau p+2\Delta t}, \dots, P_{t-\Delta t}, P_t$) from the time $t-\tau p$ when the rainfall-runoff commence in the processing unit to the time t . The total number of input is $\frac{\tau p}{\Delta t} + 1$. The second layer simulates the runoff generation in the processing unit. There are a total number of $\frac{\tau p}{\Delta t}$ neurons representing a total number of $\frac{\tau p}{\Delta t}$ runoff ($R_{t-\tau p+\Delta t}, R_{t-\tau p+2\Delta t}, \dots, R_{t-\Delta t}, R_t$) generated by rainfall within the processing time period. The neurons of the second layer are only connected with that of the first layer within the processing time period in the same processing unit (see the Fig. 2), i.e. the runoff generation at a certain time is only affected by the soil moisture at the initial time and the rainfall before that time in the same processing unit, but not by the rainfall after that time in the same processing unit and rainfall in other processing units. The third layer collects the runoff at each time step to simulate the runoff within the processing unit at the time t .

Regarding the group of upstream flow routing. In the first (input) layer, neurons from left to right in Fig. 2 are the upstream flow input ($QU_{t-\tau p}$, $QU_{t-\tau p+\Delta t}$, ..., $QU_{t-\Delta t}$, QU_t) from time $t-\tau p$ to time t , with a total number of $\frac{\tau p}{\Delta t} + 1$ input neurons. The second layer simulates river flow routing, with a total number of $\frac{\tau p}{\Delta t} + 1$ neurons representing the contribution of a number of $\frac{\tau p}{\Delta t} + 1$ flow input to the watershed outlet section at the time t . Similar to the rainfall-runoff simulation, neurons in the second layer are only connected with the neurons in the first layer at the corresponding time period of the same channel (see the Fig. 2). In the third layer, the flow at each time step is routed to the outlet section of the watershed.

Regarding the group of flow recession. In the first (input) layer, one neuron input is the discharge ($Q_{t-\tau p}$) at the outlet section of the watershed at the time $t-\tau p$. This input neuron is connected to a neuron in both the second and third layers. The recession runoff process generated by rainfall and upstream flow before the time $t-\tau p$ in the watershed is thus simulated throughout this group.

Natural watershed has good pondage action on runoff. The water storage increases when the runoff in the watershed arises, the water storage decreases when the runoff in the watershed drops. The runoff hydrograph is smoothed by normalizing the runoff process. Conceptual hydrological forecasting model often uses the function of storage to simulate the pondage action in a watershed. The ANN model lacks the storage and regulation function for the rainfall input. Output of the model has quick response to the input, which often brings sharp and rough fluctuation in the simulated hydrograph. To make up for such shortcoming of the ANN model, the arithmetic moving average process is applied before the neuron output, and the forecast flow is obtained by averaging the output of several time steps, that is,

$$QOM_i = \frac{1}{nm+1} \sum_{j=i-\frac{nm}{2}}^{i+\frac{nm}{2}} QO_j \quad (9)$$

Where, QO_j is the output of layer 4, QOM_j is the output after the moving average, nm is

a parameter.

In the MLP ANN training, the input and output data is normalized according to formula (4), and the data is also normalized in the ANN model proposed in this paper. For the commonly used sigmoid activation function, the maximum output of the ANN will not exceed the value “1” since the function has a restricted output interval of [0, 1]. Thus, in real time forecasting no matter how large the actual input value is, still the simulated flow after rescaling cannot exceed the maximum value of the training data set. This is unreasonable in real situation. Moreover, since the sigmoid activation function has an “S” shape, the function curve tends to be flat with the increase of input value, which does not conform to the law of rainfall-runoff in practice, and is difficult to accurately simulate floods of different magnitudes. The maximum value of the output of a linear function can exceed the value “1”, which better conforms to the law of rainfall-runoff process. Therefore, the linear function is chosen as the activation function of ANN in this paper.

The training algorithm in this paper is the commonly used back-propagation (BP) algorithms. The input weight (w) of neuron is calibrated iteratively through the supervised training based on measurement data. The learning process consists of two parts, that is, the forward propagation of signals and the backward propagation of errors (δ). In the forward propagation, the signal propagates upward, and the input data comes from the input layer and then output after being processed through layer 2, layer 3, layer 4 and the moving average algorithm (layer MA). Differ from the BP algorithms of MLP, the error propagates backward from the output to the layer 4 (l_4) by bypassing the moving average algorithm (layer MA), as shown in Fig. 3. The errors of neurons in the layer “ $l+1$ ” are multiplied by the input weight (W_i) and allocated to the connecting neurons of the layer l ($\delta_{li} = \delta_{l+1} \times W_{li}$). The input weight (W_{l-1}) of each neuron in layer $l-1$ connecting to the layer “ l ” is adjusted according to the neuron errors in layer l . The weight is adjusted by gradient descent method. The amount of adjustment are

281 $\Delta W_{l-1, i} = -\mu \frac{\partial \delta_l}{\partial W_{l-1, i}}$. This correction process iterates many times until the error
282 reaches an acceptable range.

283 3. Study area and model establishment

284 The study areas are the upstream of Second Songhua river in Songhua basin from the
285 Baishan reservoir to Fengman reservoir sections, and the Mozitan and Xianghongdian
286 reservoirs in the upper reaches of Pi river in Huaihe Basin. Upstream of Second
287 Songhua river located about 43 degrees North latitude, cold temperate climate, in
288 northeast China. It is a semi-humid region and mountainous area with good vegetation
289 coverage. The annual precipitation is about 750mm, among which 70% falls in rain
290 season (from June to September), and most of storm flood occur in July and August. Pi
291 river located about 31 degrees North latitude, warm temperate climate, in east China. It
292 is a humid region and mountainous area with good vegetation coverage. The annual
293 precipitation is about 1500mm, among which about 60% falls in rain season (from May
294 to September), and most of storm flood occur in from June to August.

295 The most widely applied rainfall data in real-time flood forecasting which can be
296 easily obtained from observation stations is used as the input of the model. The flood
297 forecasting model developed in this paper is an hourly model, whose time step is
298 commonly used in China.

299 From Baishan reservoir to Fengman reservoir whose river length is 194 km and
300 the basin area is 23500 km². The rainfall-runoff forecasting model is established by
301 dividing the study area into two parts, i.e., the Wudaogou drainage area and the
302 Fengman reservoir area. The river network, reservoir locations and monitoring stations
303 are shown in Fig. 4. The Wudaogou drainage area is 11600 km², and there are 10
304 precipitation stations, with one rainfall-runoff processing unit for each station, so it is
305 divided into 10 rainfall-runoff processing units. Data from 10 precipitation stations are
306 used. The Fengman reservoir drainage area is 11900 km², and there are 11 precipitation

stations, which is divided into 11 rainfall-runoff processing units. Data from 11 precipitation stations are used.

The locations of Mozitan and Xianghongdian reservoirs, its river networks, and monitoring stations are shown in Fig. 5. The Mozitan drainage area is 570 km², and there are 4 precipitation stations, which is divided into 4 rainfall-runoff processing units. Data from 4 precipitation stations are used. The Xianghongdian drainage area is 1431 km², and there are 6 precipitation stations, which is divided into 6 rainfall-runoff processing units. Data from 6 precipitation stations are used.

The model input are the *API* at the initial time of each rainfall-runoff processing units, a number of $\frac{\tau p}{\Delta t}$ interval rainfall of every processing units, and the flow at the initial time of forecast hydrological station. In addition, there are a number of $\frac{\tau p}{\Delta t} + 1$ outflow of Baishan reservoir and flow of Wudaogou station input for Fengman drainage area. The calculation method and parameters of *API* as well as the determination of τp can refer to the existing traditional hydrological forecasting scheme. There are several different unit hydrographs available for these watersheds, and the maximum value of the different unit hydrograph in the respective watershed is chosen as the parameters τp for each watershed. For the Wudaogou and Fengman drainage area, the *API* is calculated starting from 1st June, the time step of model calculation is 6-hours. For the Mozitan and Xianghongdian drainage area, the *API* is calculated starting from 1st April, the time step of model calculation is 1-hour.

For the Wudaogou and Fengman drainage area, the model is calibrated using the large scale floods data in history of the year 1957, 1960, 1964, 1971, 1975, 1991, 1994 and 1995. For the Mozitan and Xianghongdian drainage area, the model is calibrated using the large scale floods data in history of the year 2012, 2013, 2014, 2016 and 2018 for Mozitan, and 2012, 2013, 2014, 2015 and 2016 for Xianghongdian.

The ANN model was trained by the input historical flood data, i.e., the automatic calibration. During the training, the parameter *nm* of pongde action in the simulated

basin needs to be manually adjusted according to experience and calibrating results, and then restart the model training until the calibration is completed.

Recently, the Xianghongdian drainage area and Mozitan drainage area were experienced floods in year 2018 and 2020, respectively. These flood events data were used to verify the model and to obtain the forecasts from calibrated model.

The performance of model in this study was evaluated using two different standard statistical measures. The Normalized mean bias error (*NMBE*), measures the error of the simulated flood volume. The Nash coefficient (Nash and Sutcliffe, 1970), i.e. deterministic coefficient (*DC*), measures the degree of coincidence between the modeling process and the actual measurements of flood process. Calculation formulas of the *NMBE* and *DC* are as follows:

$$NMBE = \frac{\sum_{t=1}^N (QOM(t) - Q(t))}{\sum_{t=1}^N Q(t)} \times 100\% \quad (9)$$

$$DC = 1 - \frac{\sum_{t=1}^N (QOM(t) - Q(t))^2}{\sum_{t=1}^N (Q(t) - EQ)^2} \quad (10)$$

Where, $QOM(t)$ is the calculated flow from the model at time t , $Q(t)$ is the observed flow at time t , EQ is the average value of the observed flow, and N is the number of flow record in a time period.

4. Results and discussions

For the model calibration, simulated and observed discharge at Wudaogou and Fengman stations are shown in Fig. 6 (simulated in red, observed in black). discharge at Mozitan and Xianghongdian stations are shown in Fig. 7 (simulated in red, observed in black). The modeling *DC* and *NMBE* of four stations are shown in Table 1. Where, the *DC* of Wudaogou is 0.82, and the *DC* of the other three hydrological stations is greater than 0.9. The absolute value of *NMBE* of the four hydrological stations is less than 5%, that is, the absolute value of the error of simulated flood volume is less than

5%. According to China's norm of hydrological forecasting, the calibrated *DC* greater than or equal to 0.9 is considered as a class A forecasting model.

Results of verification are shown in Fig. 8 (simulated in red, observed in black). Verification of the model at Mozitan drainage area achieves good performance, where the *DC* is 0.9 and the *NMBE* is -2%, while verification of the model at Xianghongdian drainage area achieves poor performance, where the *DC* is 0.57 and the *NMBE* is -29%. Through the investigation of Xianghongdian basin, it is found that, in year 2018, a rather large water storage was available in the early stage of these projects in the basin, the discharge was increased during the flood period due to the limited storage capacity, and thus the flood peak was increased.

The uneven spatial distribution of rainstorm is always the problems to be solved in flood forecasting. In some river basins, the existing traditional models have been used to produce multiple unit hydrographs for different types of floods, which are used for forecasting according to the location of rainstorm center. The unit hydrograph is manually selected according to experience from those 3 to 11 different unit hydrographs in the traditional forecasting models of the four watersheds. This ANN rainfall-runoff operational model can automatically operation, be easy to use in flood forecasting. It is useful in flood forecasting, especially for large watershed that the heterogeneity of spatial distribution of rainfall is noteworthy. As shown in Fig. 6, Fig. 7 and Fig. 8, the model achieves good simulation and verification accuracy, and is suitable for floods of different magnitude.

The model proposed in this paper takes the initial flow of the forecast river section as the input, it degenerates into regression calculation when there is no rainfall input. Therefore, the model proposed in this paper can also be used for the forecasting of base flow. The *API* and unit hydrograph models are widely used in flood forecasting, and the operational flood forecasting schemes are usually available for the development of this model in many rivers in China and other countries.

From the perspective of conventional hydrological forecasting model, the model developed in this paper is equivalent to a model that simulates the rainfall-runoff of the basin unit by unit, automatically calibrates and calculates the runoff depth with API and rainfall, then uses the unit hydrograph for confluence calculation, and finally adds the baseflow regression calculation. From the input layer to the first hidden layer of the ANN model, it is equivalent to calculate the runoff depth of a period by multiplying the API of the unit and the rainfall of the period by different weights, which is also equivalent to the runoff depth calculation of the API model. From the second hidden layer to the third hidden layer, it is equivalent to the flow to the forecasting time calculated by multiplying the runoff depth concentration in each period by different weights, which is also equivalent to unit hydrograph calculation as shown by Hjelmfelt and Wang (1993).

Pondage action of the basin reflects the increase and decrease of the water storage in a basin with the rise and fall of flood in the process of confluence. Such regulation makes the flow process getting flat. Conceptual hydrological models such as Xinanjiang model (Zhao Ren Jun, 1992) and Sacramento Model (burnash, 1995) often use free water tank regulation to simulate pondage action. In the ANN model, the input information is instantaneously echoed by the output accordingly. In the absence of pondage action, the flow process fluctuates up and down. Therefore, in this paper, the arithmetic moving-average algorithm (MA) is applied after the output neuron before the final model output to obtain the forecast flow. In the process of model training, the parameter nm needs to be adjusted based on experience.

Neurons of the hidden layers (l_2, l_3) are only connected with the neurons of back layer with physical conception relations. It reduces the number of weight parameters (W) that needs to be trained. There are 10 rainfall-runoff unit areas in Wudaogou, each has one *API* and 14 rainfall input periods. There are 150 inputs from 10 unit areas, and one channel baseflow input in addition. The ANN model has 1506 weight parameters in total. While there would be about 23000 weight parameters if each neuron in the

back layer is connected with all the neurons in the front layer according to traditional MLP ANN connections. The neuron connections proposed in this study not only reduces the weight parameters, but also eliminates the connections of the input without physical conceptual causes. It can produce more reasonable values of weight parameters and avoid pure mathematical fitting without physical causes.

In some ANN with multiple hidden layers, the top two layers can easily over fit the training set, training error do not necessarily reveal the difficulty in optimizing the lower layers (Erhan et al., 2010). Therefore for example, dropout (Srivastava et al., 2014) and others promoted several methods to solve this problem. The ANN proposed in this paper, compared with the initial values, the weight parameters of each layer trained by the traditional BP learning algorithms are significantly improved. This can be due to the optimized connection of hidden layer neurons, which makes the error backward propagation more effectively. Generally, an initial value needs to be given before the parameter calibration starts. One disadvantage of gradient descent method is that it can't guarantee the convergence of parameters to the optimal solution, especially when the initial value is set unreasonable. Therefore, the initial value of the weights should be set at a reasonable value, such as a small positive figure.

5. Conclusions

The ANN model proposed in this paper takes the key influencing factors according to the physical process of rainfall-runoff formation, the initial Antecedent Precipitation Index (*API*), rainfall, upstream inflow and initial flow at the forecast river section as input, thus obtains a model to simulate the whole process of a flood event. The distributed rainfall is realized as the input of the model and the simulation is processed by dividing the watershed into several rainfall-runoff processing units. The model takes the data of rainfall observation station as the input and adopts the training method of machine learning, which requires less data types. It realizes a flood forecasting model

that is easy to use and practical to solve problem of the heterogeneity of spatial distribution of rainfall, and is suitable for floods of different magnitude.

This model only connects the hidden layer neuron with the input which has physical conceptual causes, as the topological structure and the information transmission process are more consistent with the physical conception of rainfall-runoff. The model with structure complying with physical conceptions achieves better results in real-time operational flood forecasting. In addition, the weight parameters of the model are reduced, so the distributed simulation of rainfall-runoff is easy to realize. The arithmetic moving-average algorithm is added to the output to simulate the pondage action of the watershed. The Back Propagation (BP) training algorithms of MLP ANN is applied in this model.

Satisfactory results have been achieved in the study areas. The model proposed in this paper can use parameters of the widely accepted traditional hydrological models, which requires less data and easy to practice in real-time operational forecasting, and can be accepted by hydrologists in real time flood forecasting.

Acknowledgements The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Table 1 *DC* and *NMBE* of model calibrating

	Wudaogou	Fengman	Mozitan	Xianghongdian
<i>DC</i>	0.82	0.92	0.90	0.91
<i>NMBE</i> (%)	0.3	0	1.5	5

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