Research on Neural Network Flood Forecasting Model Based on Hydrological Model

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Abstract: In view of the problem of inaccurate flood prediction of the current BP neural network model, establishing a neural network flood prediction model based on the random information of the hydrological model can effectively combine the advantages of various hydrological models and avoid the disadvantages of various hydrological models, so as to accurately predict the flood information. Hydrologic model randomly simulates large floods, and then inputs flood information into the neural network model, which can enhance the accuracy of flood prediction. It can also be seen from the last example that this method is more effective, and the flood prediction model based on the neural network model can be better put into application.

Keywords: BP neural network model; stochastic model; runoff forecast

1 Introduction

The difficulty of flood forecasting occurs in the nonlinear process of rainfall, and flood forecasting is even more difficult because the rainfall is not uniform. Some experts and scholars have studied different types of hydrological models for flood prediction, such as conceptual and distributed hydrological models [1]. The former mainly realizes flood prediction by homogenizing rainfall in different areas, while the latter mainly reflects the homogeneity of hydrological space and time through grid watershed, but both the former and the latter have considerable problems [2][11]. The former flood forecast is not accurate enough, the latter is not practical enough. In the meantime, the neural network model enters people's view, because of its simple structure, and does not need a lot of data as the foundation, so it can better solve the complex problems. At present, it is also widely used in hydrological forecast [3].

2 Model establishment

2.1 BP cerebellar model arithmetic computer

The information transmission system established by simulating the information of the human brain is the neural network model, where there are generally multiple hidden layers, an input

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layer and an output layer [4][12]. The neural network model mainly adopted in this paper is a three-layer error feedforward reverse neural network model, in which the neurons in any layer are disconnected with each other and only associate with the neurons in the previous layer, while the information from the input layer will enter the hidden layer after processing through the transfer function, and finally output in the output layer. Because this information is transmitted layer by layer [5], it is called a feedforward network. The transfer function, as a function of the input information, is in the most commonly used form of the sigmoid function and the linear function. The formula is as follows:

$$Y_j = f\left(\sum W_{ij} X_i - \theta_j\right) = \frac{1}{1+e^{-\left(\sum W_{ij} X_i - \theta_j\right)}} \tag{1}$$

$$Y_j = f\left(\sum W_{ij} X_i - \theta_j\right) = \sum W_{ij} X_i - \theta_j \tag{2}$$

Where Y_j is the output of the j th neuron in the neural network model, X_i is the input of the previous layer i th neuron, W_{ij} is the link weight of the j th neuron to the i th neuron in the previous layer, and θ_j is the threshold of the j th neuron. To train the neural network model and calculate its weight and threshold, it is necessary to apply the error backtransmission algorithm, take the minimum value of the error energy function E as the target function, and obtain the weight and threshold through the gradient method [6][13]. The way that E is calculated is as follows:

$$E = \frac{1}{2} \sum_t (T_t - Y_t)^2 \tag{3}$$

Where the desired and true output of the t-th neuron are T_t and Y_t, respectively.

2.2 Neural network flood prediction model

It is critical to reasonably choose the number of input factor and hidden layer neurons in the neural network flood prediction model [7]. For example, choosing the input factor requires choosing the factor with strong correlation with the output factor, while the input factor is usually the rainfall and runoff in the previous period. Assuming $\widehat{Q}(t)$ is the runoff in t, $P(t-n)$ is the rainfall during t-n, $Q(t-m)$ is the runoff in t-m, n and m are inserted into the actual data of the basin, find the model input factor with large runoff correlation, and $P(t-1), P(t-2), P(t-3), P(t-4), Q(t-1), Q(t-2)$ is obtained as follows:

$$\widehat{Q}(t) = f\left(P(t-1), P(t-2), \cdots P(t-n), Q(t-1), Q(t-2), \cdots Q(t-m)\right) \tag{4}$$

2.3 A flood prediction model of the neural network based on random information

The conceptual hydrological model can accurately describe the characteristics of rainfall-runoff process, and establish a neural network flood prediction model based on stochastic information, as shown in Figure 1.

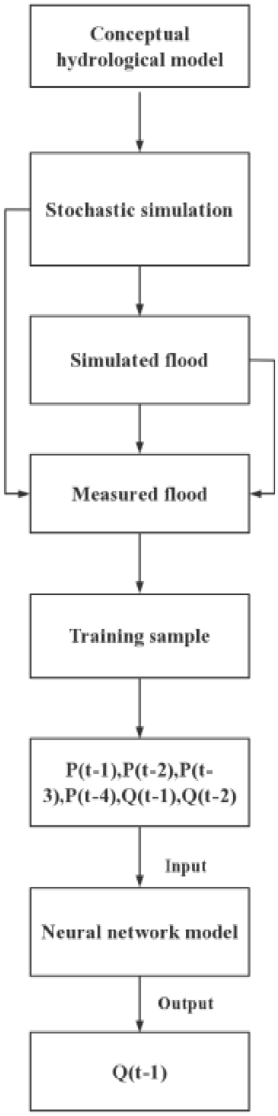

Figure 1: A flood prediction model of a neural network based on stochastic simulation information

3 Examples study

3.1 The Xin'an River model randomly simulates the rainfall runoff process

The hydrological model is used to randomly simulate the large floods and input them into the new training sample of the neural network model, increasing the specific proportion of the floods in the training sample [8]. As shown in Table 1.

Table 1: Sensitivity test of rainfall-runoff forecast accuracy of Xin-an River model on starting conditions

Flood	Number of flood sites	Mean value of peak error variation VEQ / (%)	Peak time error change mean vet / period	Mean value of uncertainty coefficient variation VDC
Total flood	45	15.9	0.094	0.134
Big flood	15	7.4	0.068	0.061
Small flood	30	19.8	0.107	0.169

Secondly, the stability of the model was tested to simulate two sets of floods, each with ten fields. The details are shown in the table below.

Table 2: Stochastic simulated flood information tables for groups 1 and 2

Group I random flood			
Flood serial number	Cumulative rainfall/mm	Number of rainfall periods/6h	Peak discharge/(m^3/s)
1	110	6	2513
2	120	7	2613
3	114	4	2700
4	107	6	2125
5	124	11	2980
6	140	10	3430
7	141	14	3570
8	182	13	5012
9	195	14	5140
10	220	15	7041

Group II random flood			
Flood serial number	Cumulative rainfall/mm	Number of rainfall periods/6h	Peak discharge/(m^3/s)
1	107	6	2379
2	108	4	2713
3	110	6	2873
4	120	8	2430
5	124	6	2540
6	116	7	3012
7	130	9	4013
8	131	11	4125
9	161	13	4682
10	217	16	7196

3.2 Neural network model after expanding the training sample with the stochastic simulation information of the conceptual model

The two sets of floods randomly simulated in Table 2 were trained as the neural network model samples, and the latter 16 fields were resimulated, and the results are shown in the following Table 3. Where model A is no stochastic simulation information, and B and C are the training samples in the first and second random floods, respectively [9].

Table 3 Simulation results of 16 floods by three neural network models

Flood	Mean value of flood peak relative error/ (100%)		
	Model A	Model B	Model C
Total flood	12.1	9.1	9.2

big flood	14.2	10.8	12.3
Small flood	8.0	8.1	8.3
Flood	Peak time error mean/period		
	Model A	Model B	Model C
Total flood	0.66	0.52	0.51
big flood	0.62	0.51	0.53
Small flood	0.51	0.52	0.57
Flood	Mean value of certainty coefficient		
	Model A	Model B	Model C
Total flood	0.812	0.817	0.891
big flood	0.971	0.901	0.912
Small flood	0.846	0.843	0.820

As can be seen from the data above, models B and C have high simulation accuracy, especially for large floods, so it also proves that the prediction accuracy of large floods can be effectively improved by adding simulated flooding to the training samples [10].

4 Conclusion

Neural network model has some advantages over other hydrological models, but the forecast results are not accurate enough because it cannot accurately reflect the rainfall-runoff mechanism and lacks the flood factors in the training samples. In order to obtain more accurate forecast results, this paper establishes a neural network flood prediction model based on stochastic simulation information, extracts the advantages of the neural network model, and accurately simulates the large and small floods. Examples also prove that the model can effectively improve the accuracy of flood prediction.

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