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A FORECASTING MODEL OF DELTA EVOLUTION USING ARTIFICIAL NEURAL NETWORKS

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Abstract: The coastal zone is an area that has the most active land-ocean interaction. Its evolution takes in high complexity, fuzziness and non-linearity under the influence of many factors such as the coming water and sediment, marine dynamics, sea-floor terrain, crust movement, climatic change and human activities etc. Considering the ability of the neural network on non-linear problems, a BP model to predict the sub-delta evolution is established. Meanwhile, the scheme and coefficients of the network are investigated in this paper. Taking Huanghe Sub-delta as an example, its area and shoreline change are studied. The results indicate that the computed and the measured are in a good agreement. It is also proved that the artificial neural network can be perfectly used to forecast the evolution of the delta.

Key words: The coastal zone; Artificial neural network; BP model; Beach processes; "Trial-error" method; Huanghe Delta

1. INTRODUCTON

Trying to forecast the delta evolution process is a complex activity as it is influenced by a number of factors such as the coming water and sediment, marine dynamics, sea-floor terrain, crust movement, climatic change and human activities etc. However, this kind of forecasting is particularly important as it directly affects estuarine governing, delta development, petroleum exploitation and so on. Hence, it is a hot point problem for researchers all the time.

The studies of delta evolution forecasting have progressed rapidly, many methods have been proposed as yet— For example, numerical model, physical model, data analysis, and gray model and so on. All these methods have their own faults. Take the numerical model as an example, it is one of the most common used methods by now. But because of the complexity of water and sediment boundary, it is very difficult to take various random factors into consideration. Hence, in order to better forecast the change of delta and afford technical support to engineering projects, it is essential to find another more effective method. Based on the analysis of non-linear characteristics of delta evolution, the artificial neural networks are used in this paper to attempt to improve the ability of forecasting.

2. ARTIFICIAL NEURAL NETWORKS

In order to be able to apply appropriate neural networks to particular problems, it is important to have an understanding of the broad range of networks that are now available and how these networks are trained. Artificial neural network is a non-linear information processing system that imitates the structure and function of human brain; it has very strong nonlinear mapping and self-reliance, self-organizing, self-learning ability. According to the differences of learning rules, artificial neural networks can be branched out into many kinds in which the BP model is the most common employed.

BP network is a multi-layer feed-forward network based on the error back propagation algorithm. It involves input-layer, hidden-layer and out-layer and can be used to achieve any non-linear mapping. A typical BP model contains two parts, one is information feed-forward propagation process and the other is error back propagation process. The logarithmic Sigmoid function is always employed in the network nodes which can be expressed as follows:

$$y = f(x) = \frac{1}{1+e^{-x}} \tag{1}$$

A typical BP network structure (three layers) is shown in Fig.1.

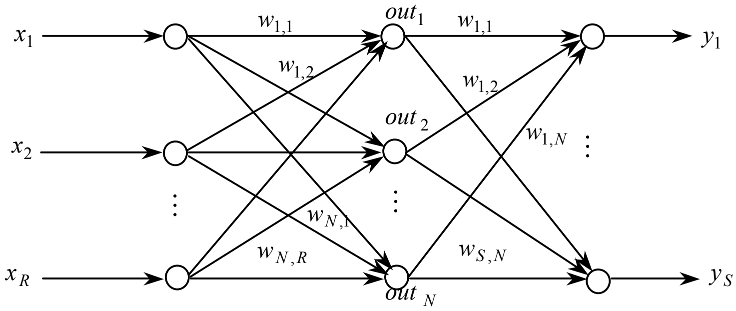

Fig. 1 Structure chart of BP network

2.1 INFORMATION FEED-FORWARD PROPAGATION PROCESS

In this course, information propagates from the input-layer to the out-layer through the hidden-layer. As for *p*th group of specimen, assume that input elements of *R* dimensions are as $x_{1p}, x_{2p}, \cdots, x_{Rp}$, and then the input of *j*th node in the hidden-layer is

$$net_{jp} = \sum_{i=1}^{R} w_{ji} x_{ip} + b_j \tag{2}$$

The output of the *j*th node can be obtained:

$$out_{jp} = f(net_{jp}) = [1+\exp(-net_{jp})]^{-1} \quad (j = 1,2,\cdots,N) \tag{3}$$

And so, we can get the input of the *k*th node in the output layer:

$$net_{kp} = \sum_{j=1}^{N} w_{kj} out_{jp} + b_k \quad (k = 1,2,\cdots,S) \tag{4}$$

The *k*th node has the output as

$$y_{kp} = f(net_{kp}) = [1+\exp(-net_{kp})]^{-1} \quad (k = 1,2,\cdots,S) \tag{5}$$

In which w, b are weights and bias of the networks, respectively.

2.2 ERROR BACK PROPAGATION PROCESS

The BP model is based on the error back propagation as mentioned above, so it is trained by the Delta learning algorithm. After the above course, the outputs of networks are as y_{kp}. Assume that the expected output is t_{kp}, M is the number of samples, then the mean squared error is as follows:

$$E = \frac{1}{M}\sum_{p=1}^{M} E_p = \frac{1}{M}\sum_{p=1}^{M}\left(\frac{1}{2}\sum_{k=1}^{S}(t_{kp} - y_{kp})^2\right) \tag{6}$$

Weights and bias of the networks are modified using the Delta algorithm, they are given by

$$\Delta_p w_{ji}(t+1) = \eta\delta_{jp} out_{jp} + m\Delta_p w_{ji}(t) \tag{7}$$

$$\Delta_p b_j(t+1) = \eta\delta_{jp} + m\Delta_p b_j(t) \tag{8}$$

In which η is the learning rate; m is the momentum coefficient, the δ error can be expressed as follows:

Output-layer $$\delta_{kp} = y_{kp}(1-y_{kp})(t_{kp} - y_{kp}) \tag{9}$$

Hidden-layer $$\delta_{jp} = out_{jp}(1 - out_{jp})\sum_k \delta_{kp} w_{kj} \tag{10}$$

The modification of the weights and bias:

$$w_{ji}(t+1) = w_{ji}(t) + \eta \sum \delta_{jp} out_{jp} + m[w_{ji}(t) - w_{ji}(t-1)] \tag{11}$$

$$b_j(t+1) = b_j(t) + \eta \sum \delta_{jp} + m[b_j(t) - b_j(t-1)] \tag{12}$$

According to the above discussion, we can get the computation flow chart as shown in Fig.2.

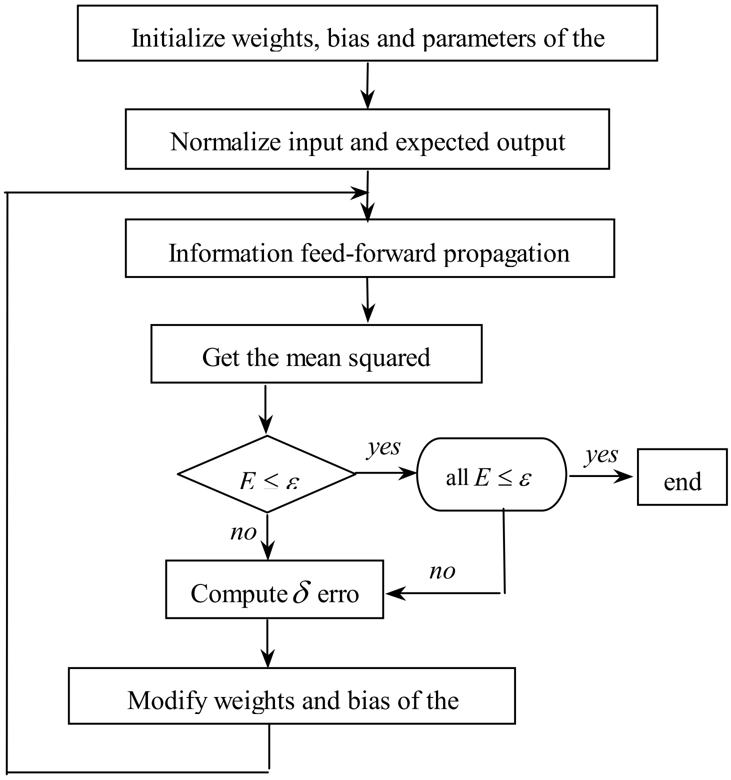

Fig. 2 Computation flow chart of BP network

3. DELTA EVOLUTION PREDICTION USING BP MODEL

As mentioned before, it is vital to study the delta evolution because various aspects of delta development have relation with it. And now the most difficult problem in this study is the forecasting problem. For this, researchers of various countries have proposed many methods. According to the analysis of delta evolution feature, the method of using artificial neural networks to study this problem is proposed and the Huanghe sub-delta is taken as an example.

Delta evolution prediction always refers to the area and shoreline forecasting. The area and shoreline of Huanghe delta are affected by many factors, their evolutions are very intricate and the mechanism is very difficult to analyze. Due to the weakness of the marine dynamics, the coming water and sediment of the upper reach are chosen as the input elements of the network, and the area and shoreline change are studied in this paper.

3.1 EXPERIMENTS 1——AREA MODEL

14 samples of the Huanghe sub-delta area and the coming water and sediment discharges from 1976 to 1989 were collected as the model data, where the fore-twelve data are as the training data and the step-two data are taken as the compared data. As the function of the node of BP model is logarithmic Sigmoid, its mapping interval is [0,1] and can't map any values. In order to resolve this problem, the input and expected output samples should be normalized. The following equation is employed in this paper:

$$T = \frac{X - X_{\min}}{X_{\max} - X_{\min}}\beta + \xi \qquad (16)$$

Where T and X are the values after and before normalization, respectively. β and ξ are parameters, β is always set as 0.9, $\xi = (1-\beta)/2$.

As for the determinations of the structure and parameters of the model, there is still no inductive theory. The "trial-error" method is used in this paper. After several times attempts, the two hidden-layers structure of 3-14-7-1 are employed, and the learning rate, learning rate descending ratio, momentum coefficient are set as 0.01,0.7,0.5, respectively. The permissible error is 1E-5. The model reached the permissible error after 2060 steps training, shown in Fig.3. The results are shown in Fig.4 and Table 1.

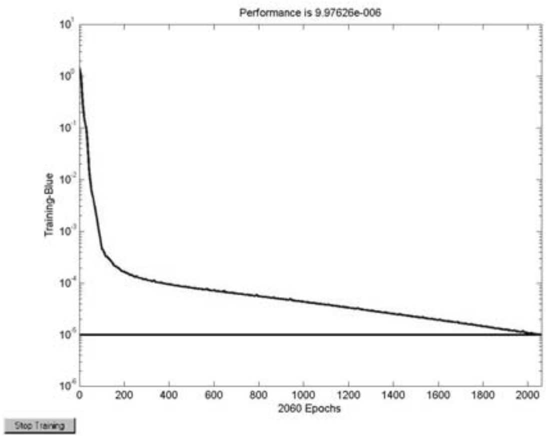

Fig. 3 Sketch of training error descending

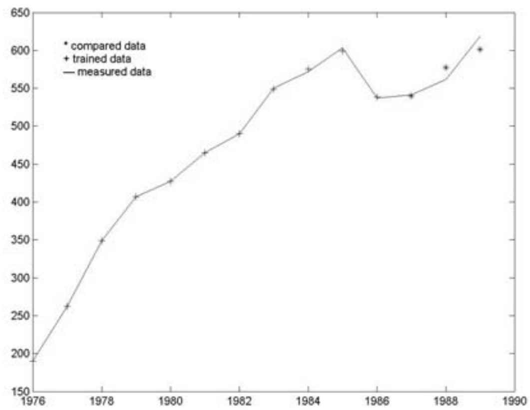

Fig. 4 Results of the BP model

Table 1 Comparison of the modeled and the measured

Year	Measured data (km^2)	Modeled data (km^2)	Error (km^2)	Error rate (%)
1976	190	190.0345	0.0345	0.018
1977	262	262.1083	0.1083	0.041
1978	349	348.9622	-0.0378	0.011
1979	407	407.0353	0.0353	0.009
1980	427	427.0404	0.0404	0.009
1981	465	465.1003	0.1003	0.022
1982	490	489.8066	-0.1934	0.039
1983	550	548.9930	-1.007	0.183
1984	572	575.1990	3.1990	0.559
1985	603	599.5091	-3.4909	0.579
1986	537	538.5216	1.5216	0.283
1987	541	539.8776	-1.1224	0.207
1988	562	577.5899	15.5899	2.774
1989	618	601.3818	-16.6182	2.689

From the Fig.4 and Table 1, we can see that the modeled and the measured have a good agreement. The mean training error is 0.163%, the biggest training error is 0.579%. Two errors of the compared data are 2.774% and 2.689%, respectively. They are all less than 5% and can satisfy the demands of engineering projects. These results indicate that the BP model can be used to forecast area change under the condition of giving suited structure and parameters.

3.2 EXPERIMENTS 2——SHORELINE PREDICTION

Shoreline prediction is very important for the delta development. As for the Huanghe sub-delta, the study area in this paper is shown in Fig.5. The 8 rays from point O are taken as test-lines. If we can forecast the distance between point O and shoreline, the delta evolution can be determined. The test-line O-6 is taken as an example to see whether the BP model can be used in this area.

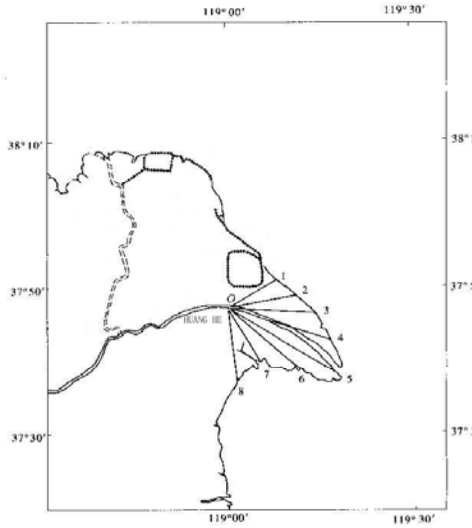

Fig. 5 Study area and layout of test-line

The shoreline model has the same input factors as the area model. Eq.(16) is still used to standardized the samples, the structure and parameters are determined by the "trial-error" method. After several times attempts, the two hidden-layers structure of 3-20-14-1 are employed, and the learning rate, learning rate descending ratio, momentum coefficient are set as 0.01,0.8,0.4, respectively. The permissible error is 1E-5. The model reached the permissible error after 522 steps training, shown in Fig.6. The results are shown in Fig.7 and Table 2.

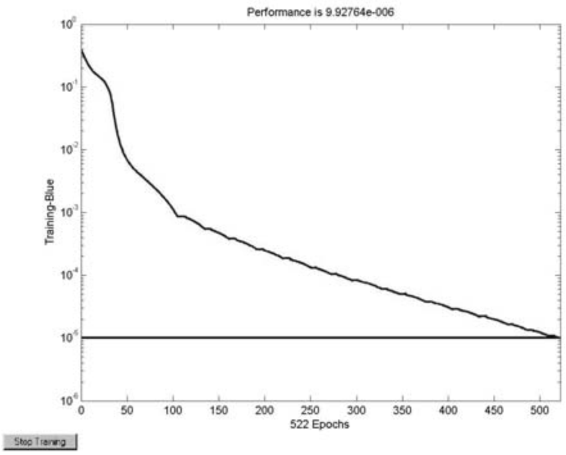

Fig. 6 Sketch of training error descending

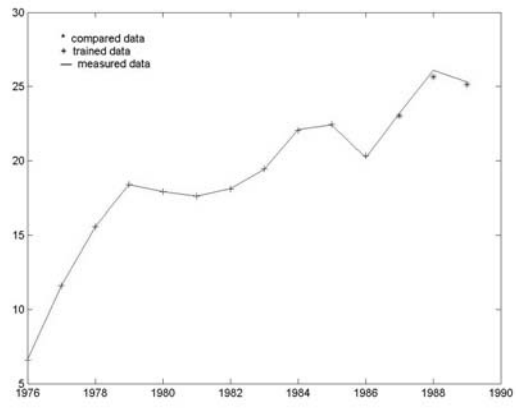

Fig. 7 Results of the BP model

From the Fig.7 and Table 2, we can see that the modeled and the measured have a good agreement. The mean training error is 0.202%, the biggest training error is 0.785%. Two errors of the compared data are 1.769% and 0.658%, respectively. They are all less than 5% and can satisfy the demands of engineering projects. These results indicate that the BP model can be used to forecast shoreline evolution under the condition of giving suited structure and parameters.

Table 2 Comparison of the modeled and the measured

Year	Measured data (km^2)	Modeled data (km^2)	Error (km^2)	Error rate (%)
1976	6.6	6.5979	-0.0021	0.032
1977	11.6	11.6097	0.0097	0.084
1978	15.6	15.5888	-0.0112	0.072
1979	18.4	18.4032	0.0032	0.017
1980	17.9	17.8949	-0.0051	0.028
1981	17.6	17.5872	-0.0128	0.073
1982	18.1	18.0922	-0.0078	0.043
1983	19.4	19.4469	0.0469	0.242
1984	22.1	22.0305	-0.0695	0.314
1985	22.4	22.4305	0.0305	0.136
1986	20.2	20.3197	0.1197	0.592
1987	23.2	23.0179	-0.1821	0.785
1988	26.1	25.6383	-0.4617	1.769
1989	25.3	25.1335	-0.1665	0.658

4. CONCLUSION

Delta evolution is a very intricate non-linear system. It is influenced by many factors such as the coming water and sediment discharges, coastal dynamics etc. The dynamics in Huanghe mouth is very weak, so it is not considered and the coming water and sediment discharges are taken as the input factors. The results of models show that the computed and the measured have a good agreement. It is also proved that the artificial neural networks can be perfectly used to forecast the delta evolution under the condition of giving suited structure and parameters. At the same time, it is necessary to take a more general consideration of the influencing factors to improve the ability of prediction.

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