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Analysis on the Stability of Reservoir Soil Slope Based on Fuzzy Artificial Neural Network

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Abstract: Owing to the fact that the relation between the reservoir soil slope stability and its influencing factors is complicated and fuzzy, a method-fuzzy neural network to analyze the reservoir soil slope stability is proposed. The method infuses fuzzy reasoning process into the structure of neural network, makes the physical meaning of neuron and weight of neural network clear, reduces the process of regulation match, raises the speed of reasoning and improves greatly the self-adaption capacity of the system. In the end, the fuzzy neural network model is trained and tested by the collected 21 cases of soil slope data samples. The result proves that the fuzzy neural network is a valid method, which has significant advantages over general BP neural network model in analyzing effectiveness and quality.

Keywords: Fuzzy theory, neural network, soil slope, stability

INTRODUCTION

Up to now, more than 80,000 reservoirs of all kinds have been established in China, ranked the first in amount all around the world. However, over 37,000 of them are dangerous reservoirs that can't function effectively but have the danger of collapse instead, which does great harm to social public security and economic sustainable development. And the instability of reservoir slope is one of the main reasons causing collapsing. There are varied factors influencing reservoir slope stability, whose influence on the reservoir slope stability is a nonlinear complicated process. Most of the influence has undetermined features like being stochastic and fuzzy. Therefore, it's rather difficult to exactly evaluate the stability of reservoir slope. At present, the major methods to study slope stability are limit equilibrium method, numerical analysis method, grey system method1, fuzzy comprehensive evaluation (Wei and Li, 1996; Li *et al*., 1998; Wei, 1994; Zhao *et al*., 2004) and neural-net algorithms etc. However, the evaluation results are always not so satisfactory because of the limitation of all methods themselves (Xia and Li, 2002). Under this circumstance, this study proposes a fuzzy artificial neural network method that can process determined and undetermined information simultaneously. By the pre-process of input knowledge and the after-treatment of output knowledge, the model involves fuzzy logical reasoning into the nonlinear algorithm of neural network and fuzzy evaluation is achieved by neural network.

STRUCTURE OF FUZZY NEURAL NETWORK

This study makes general BP neural network fuzzy. To be specific, on the basis of reserving original structure of neural network, neuron is fuzzily processed directly. In other words, input value or weight value are changed to fuzzy quantity expressed by membership grade; by network study, the output fuzzy sub-collection is diverted to non-fuzzy digital quantity. The specific model of fuzzy neuron is a multi-input but single-output five-layer fuzzy neural network, with its topological structure as Fig. 1.

The first layer is the input layer: In the layer, every neuron refers to one input variable, that is, one factor influencing the stability of reservoir slope. The neuron in this layer sends the input value to the neuron in the next layer directly as follows:

$$I^{(1)}_h = X_h,\ O^{(1)}_h = I^{(1)}_h \quad (1)$$

In which: $h = 1, 2, \ldots m$, m refers to m input variables.

The second layer is the fuzzy layer: Clear input variables in the previous layer will become fuzzy here. The connection weight between neuron in this layer and that of the previous layer is 1, using trapezium distribution for the membership function of every neuron. The relationship between the input and output is as follows:

$$I^{(2)}_i = O^{(1)}_h,\ O^{(2)}_i = U(u) \quad (2)$$

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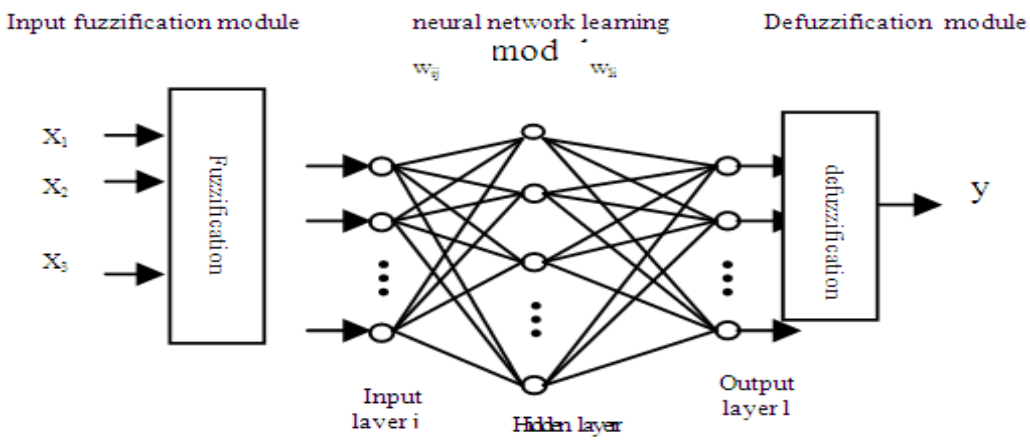


Fig. 1: The structure design of fuzzy neural network

where, $U(u)$ refers to the trapezium membership function, with the formula as:

$$\mu(x)=\begin{cases}1, & 0\le x\le a\\ \dfrac{b-x}{b-a}, & a\le x\le b\\ 0, & x>b\end{cases} \tag{3}$$

$$\mu(x)=\begin{cases}0, & x<a\\ \dfrac{x-a}{b-a}, & a\le x\le b\\ 1, & x>b\end{cases} \tag{4}$$

The value of a and b in formula (3) and (4) is determined by the value range of the case index. As for the input sample data, if it belongs to quantitative data, it will be fuzzily processed by the above membership function; if it belongs to qualitative data (discrete type), it will be fuzzily processed by the application of experience assignment method.

The third layer is the regulation layer: The connection strength between the neuron in this layer and that of the second layer is 1, regular neuron accomplishing the fuzzy logical "YU" operation, namely:

$$o_j^{(3)} = \min_{i\in I_j}(o_i^{(2)}) \tag{5}$$

In formula (5), I_j refers to the subscript collection of the neuron in the second layer which is connected to the number j neuron in the third layer. $O^{(2)}{}_I$ refers to the output of the number i neuron in the second layer.

The fourth layer is the output layer of neural network: In this layer, the membership function of every neuron has trapezium distribution and the initial connection weight to the neuron in the third layer is stochastically selected in the range of [-1, 1]. The activation degree of every regulation is determined by the square of the weight. The function in this layer is like the following:

$$o_k^{(4)} = \max_{j\in I_k}(o_j^{(3)} w_{kj}^2) \tag{6}$$

In formula (6) I_k refers to the subscript collection of all the neuron in the third layer connected to the number k neuron in this layer.

The fifth layer is the layer of deblurring: The function of this layer is deblurring, the deblurring of output knowledge is analyzed by the application of single fuzzy collection method and the principle of largest membership grade II[8].

In which: $A_1, A_2, \ldots, A_n$ refers to n observation points; $C_1, C_2, \ldots, C_m$ refers to m attributes; x_{ij} refers to the value of attribute number i from observation point number j; ω refers to weight vector, ω_k refers to the weight of observation number k.

CASE STUDY OF RESERVOIR SOIL SLOPE STABILITY

Analysis of the factors influencing reservoir soil slope stability: The analysis and statistic of the factors influencing reservoir soil slope stability prove that the stability condition is the result of multi-factors' nonlinear comprehensive function. Therefore, according to the result of the comprehensive influence of multi-factors on reservoir soil slope stability, they can be classified into 8 indices:

Table 1: Simulation result of engineering cases and network models of the reservoir slope

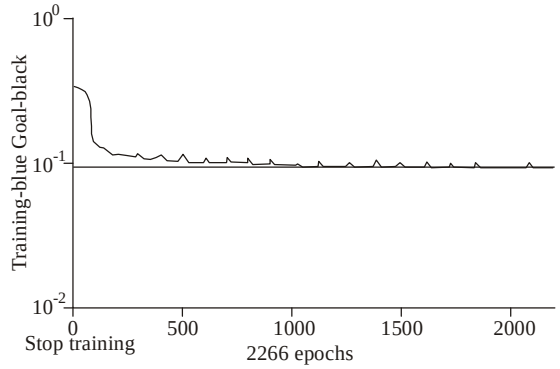
Serial number of cases	X1 (m)	X2 KN/m^3	X3 (KPa)	X4 (°)	X5	X6 (°)	K (cm/s)	v	Safety coefficient	Slope condition	Model condition	Calculation result
1	150	22.44	0.00	35.00	0.25	23.75	0.084	6.8	0.912	Unstable	Training	0.912
2	150	22.44	0.00	35.00	0.25	23.75	0.200	6.8	0.798	Unstable	Training	0.798
3	150	22.44	0.00	35.00	0.25	23.75	0.137	6.8	1.235	Stable	Training	1.235
4	150	22.44	0.00	35.00	0.25	23.75	0.200	6.8	1.189	Stable	Training	1.189
5	78	23.00	0.00	40.00	0.22	26.50	0.060	1.0	1.465	Stable	Training	1.465
6	46	19.80	0.00	32.00	0.25	26.50	0.060	3.0	1.011	Stable	Training	1.011
7	46	19.80	0.00	32.00	0.25	21.80	0.060	3.0	1.028	Stable	Training	1.028
8	39	20.19	9.80	21.00	0.25	19.29	0.047	0.3	0.981	Unstable	Training	0.981
9	73	22.44	0.00	35.00	0.25	18.43	0.141	2.9	1.125	Stable	Training	1.125
10	38	18.13	10.0	24.25	0.40	17.07	0.002	1.0	1.122	Stable	Training	1.122
11	54	20.90	11.9	20.40	0.75	21.04	0.020	0.7	1.080	Stable	Training	1.080
12	53	19.60	5.00	26.50	0.40	15.52	0.007	2.7	0.841	Unstable	Training	0.841
13	53	19.60	5.00	22.00	0.40	15.52	0.007	2.7	0.754	Unstable	Training	0.754
14	51	17.35	20.0	24.00	0.40	18.43	0.104	3.1	0.961	Unstable	Training	0.961
15	51	17.88	21.2	13.92	0.40	18.43	0.104	3.1	1.056	Stable	Training	1.056
16	40	18.66	8.00	26.00	0.40	21.80	0.007	0.5	0.909	Unstable	Training	0.909
17	40	18.66	8.00	26.00	0.40	21.80	0.007	0.6	0.934	Unstable	Testing	0.929
18	40	18.00	21.0	21.33	0.40	21.80	0.007	0.2	0.938	Unstable	Testing	0.935
19	9	19.60	10.0	16.00	0.40	21.80	0.002	12.0	1.346	Stable	Testing	1.345
20	9	19.60	10.0	8.000	0.40	21.80	0.002	12.0	1.049	Stable	Testing	1.046
21	15	18.42	14.95	21.20	0.40	45.00	0.104	21.0	1.051	Stable	Testing	1.054

Case 1 to 4: Comes from Huang He Xiao Lang Di Reservoir; Case 5: Comes from Xin Jiang Xia Ban Reservoir; Case 6 and 7: Comes from Tong Cheng Jing Zhu Miao Reservoir; Case 8 and 9: Comes from Yue Cheng Reservoir; Case 10: Comes from Qing Hai Gu Shan Reservoir; Case 11: Comes from Jiangxi Lao Bu Reservoir; Case 12 and 13: Comes from Shanxi Yu He Reservoir; Case 14 and 15: Comes from Fujian Hong Wu Yi Reservoir; Case 16 to 18: Comes from Fujian Ling Li Reservoir; Case 19 and 20: Comes from Zhejiang seawall; Case 21: Comes from Hunan An Xiang Reservoir

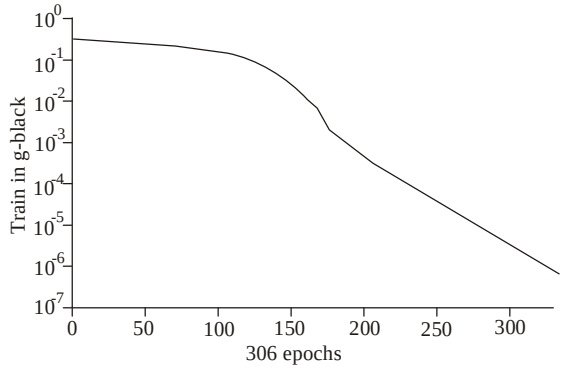
- The height of the reservoir slope X1
- The weight of the reservoir slope X2
- The cohesiveness of the reservoir slope X3
- The internal frictional angel of the reservoir slope X4
- The pore pressure ratio of the reservoir slope X5
- The slope angle of the reservoir slope X6
- The permeability coefficient of the reservoir slope K
- The drop speed of water level V[10]

Model sample data: The study collects 21 cases of reservoir slope from reference[9], among which 12 are stable slopes and the other 9 are unstable ones, as shown in Table 1.

Determination of the membership grade of input variables: Given the height of the reservoir slope [a, b] = [9,150] and its membership function formula (3); the weight of the reservoir slope [a, b] = [17.35, 22.14] and its membership function formula (3); the cohesiveness of the reservoir slope [a, b] = [0.21, 2] and its membership function formula (4); the internal frictional angle [a, b] = [8, 40] and its membership function formula (4); the pore pressure ratio of the reservoir slope [a, b] = [0.25, 0.75] and its membership function formula (3); the slope angle of the reservoir slope [a, b] = [15.52, 45] and its membership function formula (3); the permeability coefficient of the reservoir slope k [a, b] = [0.002, 0.200] and its membership function formula; the drop speed of water level V [a, b] = [0.2, 21.0] and its membership function formula (3).



(a) BP algorithm (2266 times) learning curve

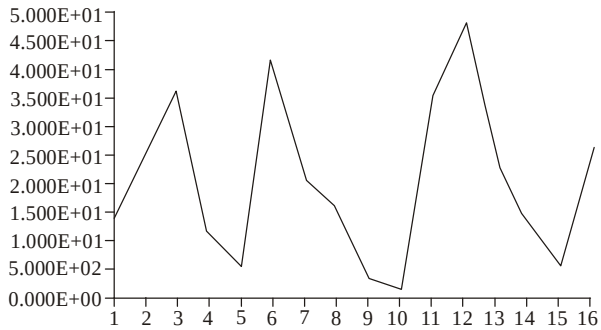


(b) Fuzzy BP algorithm learning curve

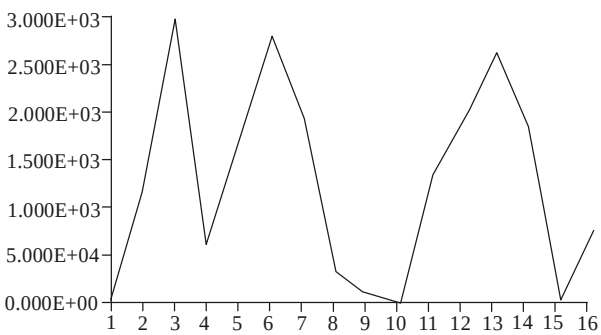
Fig. 2: Result of simulation

Table 2: The comparison of the testing results of reservoir soil slope stability coefficient based on BP neural network model and fuzzy neural network model

Serial number of the testing sample	Actual situation		BP neural network model			Fuzzy neural network model		
	Actual safety coefficient	Actual condition of the slope	Estimated safety coefficient	Comparative error (%)	Slope condition	Estimated safety coefficient	Comparative error (%)	Slope condition
17	0.934	Unstable	0.945	1.18	Unstable	0.929	0.54	Unstable
18	0.938	Unstable	0.972	3.62	Unstable	0.935	0.32	Unstable
19	1.346	Stable	1.306	2.97	Stable	1.345	0.07	Stable
20	1.049	Stable	0.987	5.91	Unstable	1.046	0.29	Stable
21	1.051	Stable	1.021	2.85	Stable	1.054	0.29	Stable



(a) Training-error curve of BP neural network



(b) Training-error curve of fuzzy neural network

Fig. 3: Training-error curve

The training and testing of network model: The study takes the above 8 influencing factors as the input variable of neural network and the stability coefficient of the reservoir slope as the output variable. Studying and training are processed by the application of the 16 practical engineering cases in sample Table 1 until the output error reaches the standard. By the application of the 5 engineering cases in sample Table 1, testing is processed to cross validate the fuzzy reasoning model. The result of the training and testing can be seen in Table 1.

If the sample is trained by traditional BP neural network model, the accuracy of the error can reach 0.1 after 2266 times of training. However, the accuracy of the error can reach 10^{-6} only after 300 times of training by the current fuzzy neural network. The specific training process of the network model can be seen in Fig. 2 and Table 2.

Evaluation of the model: The error curve of network model after 300 times of training is shown in Fig. 3.

CONCLUSION

On the basis of the previous evaluating theories and methods of slope stability, the study analyzes the reservoir soil slope stability by the application of thecombined method of fuzzy theory and neural network. The result of the study proves:

- Fuzzy neural network method can adequately approximate complicated nonlinear relation and simulate dynamic characteristics conforming to undetermined system. Fuzzy neural network can solve the complicated problem of being undetermined and nonlinear.
- The soil slope stability of some reservoirs are estimated by fuzzy neural network. And the result of the estimation conforms to that of the actual result, which shows that fuzzy neural network can be applied to qualitatively estimate the reservoir soil slope stability, being convenient, practical and valid as well.
- Owing to the complicated nonlinear relation among factors influencing the reservoir slope stability and the many decisive geologic factors they include, the analysis of the reservoir soil slope stability by fuzzy neural network is significantly better in speed and accuracy that that of general BP neural network model when compared.

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