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Application of Artificial Neural Networks to the Classification of Coal Reserve Assets*

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Abstract: Using the classification results by the fuzzy clustering models as the basis for choosing the training patterns, a feed forward networks model for classification is given. Remarkable success was achieved in training the networks to learn the patterns and in classifying the coal reserve assets. The results show that the neural network approach for classification has some advantages such as stability and reliability.

Key words: coal reserve assets, neural networks, training, classification

This paper proposes an artificial neural network (B-P network) model for the classification of coal reserve assets, and data from 77 mines are used for the illustration of modeling and classification. The training samples employ the canonical cases of the classification results by the fuzzy clustering model. At last, the results by artificial neural networks method are compared with the those by the fuzzy model, and are shown to conform to reality. At the same time, the method remedies the defect of the fuzzy method.

1 Neural Network Model for the Classification of Coal Reserve Assets[1~3]

1.1 Background of problem

Because the value of coal reserve asset is influenced by many factors, to classify coal reserve assets is a synthetic evaluation problem of multi-factors and multi--levels. These factors can be divide into three categories, that is in geology, technology, social-economy. By discussing factors with relative experts many times, main influencing factors are selected from these factors. Their evaluation index system is shown in Fig. 1. The data in the Fig. 1 are the weights of every factors determined when classifying by the fuzzy method.

On the basis of the evaluation index system, a fuzzy clustering model was originally used to classify the coal reserve assets from 77 mines. Though the results tallied with the actual situations, there was some subjectiveness in the determination of the membership degree for every factor to different class and the weights of every factor. These defect can be made up by the artificial neural networks. Therefore, it is possible and necessary to set up the artificial neural network model for classification.

1.2 Artificial neural network

An artificial neural network is a non-linear dynamic system that contains many simple non-linear calculation units and connection nodes. According to the different characteristics of neural networks for classification, we employ multilayer feedforward networks. In the type of network, each layer consists of many connection nodes. Every connection node in the *k*th layer links with each connection node (neuron) in the (*k*+1)th layer. The first is input layer, and the last is output layer. The n-n_1-m network is shown in Fig. 2, where n is the number of neurons in the input layer, n_1 is the number of the neurons in the hidden layer, and m is the number of neuron in output layer. Each connection node corresponds to a weight. By modifying these weights tothe network, the network function reflecting from input to output is modified.

According to the different character of the system, the hidden layer and output layer all employ the following character function

$$f(u_i) = \frac{1}{1+e^{-u}} = \frac{1}{1+e^{-(\sum w_{ij} x_j - \theta)}}$$

where w_{ij} is weight, θ_i is threshold, and i, j are the signs of nodes.

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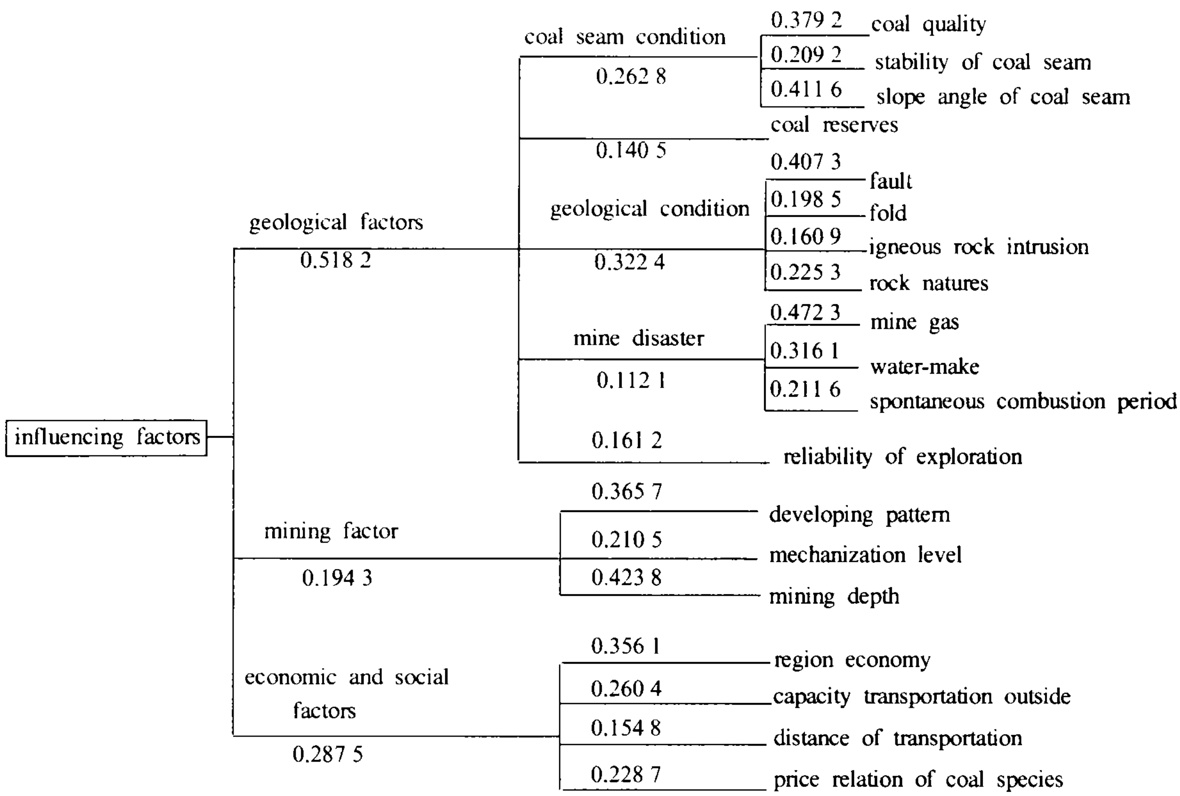

Fig.1 Evaluation index system of influencing factors

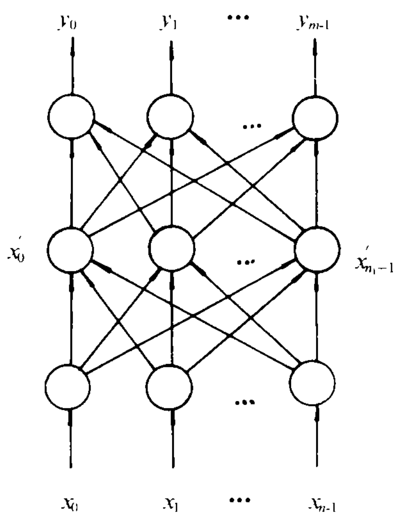

Fig.2 Multi-layer feed forward neural network model

1.3 Training algorithm of neural network

In the paper, Back-Propagation algorithm for errors is employed to train feedforward networks. B-P algorithm's advantages lie in its parallel structure and the parameter flow from input to output. Suppose that the numbers of input learning samples are p: x^1, x^2, $\cdots$, x^p, and their corresponding target values of output are t^1, t^2, $\cdots$, t^p. The training algorithm compares the real output y^1, y^2, $\cdots$, y^p with t^1, t^2, $\cdots$, t^p to modify their connection weights and threshold according to both's error, and enable y^{p_1} to approach the target value t^{p_1} possibly. Based on gradient-descent method, the algorithm often appears to converge in part region, and its converging speed is slow. Therefore, we employ the improved B-P algorithm. Its steps are as follows:

(1) Hoses initial weight vector $w_{ij}(0)$ adopts a random variable as initial value of weight and threshold in each layer.

$w_{sq}(0)$ = Random(•), where sq is ij, jk.

(2) In the known p training samples, each pattern of training set is used in succession to clamp the input and output layers of the network shown in Fig. 2. At first an input p_1=1 is selected.

(3) Calculates the output x_j, y_k in each layer

$$x_j = f(\sum_{i=0}^{n_1-1} w_{ij} x_i) \quad (1)$$

$$y_k = f(\sum_{i=0}^{m-1} w_{ij} x_j) \quad (2)$$

For convenience, the thresholds are put in connection weights in formula (1) and (2).

(4) Calculates each layer's errors for output targets

of known sample by the following formula:

$$\delta_{jk}^{p_1} = (t^{p_1} - y_k^{p_1})y_k^{p_1}(1 - y_k^{p_1}) \quad (3)$$

$$\delta_{ij}^{p_1} = \sum_{k=0}^{n_1-1} \delta_{jk}^{p_1} w_{jk} x_j^{p_1}(1 - x_j^{p_1}) \quad (4)$$

then stores every value of $x_j^{p_1}$, $x_i^{p_1}$.

(5) The times p_1 how many sample sets learned are added and p_1+1 is stored. If $p_1+1<p$, goes to step (2) to calculate continuously. Otherwise, starts with the first input sample $p_1=1$, and goes to step (6).

(6) Weights and thresholds are calculated by the following formula. In order to avoid converging in part region, and make convergence speed fast, in 1986 Lomenhate, Hinton and Williamus proposed a modified algorithm for training, which adds an adjusting term called momentum. The adjusting formula is rewritten as follows:

$$w_{jk}(n_0 + 1) = w_{jk}(n_0) + \eta \sum_{p_1=1}^{p} \delta_{jk}^{p_1} x_j^{p_1} + \alpha(w_{jk}(n_0) - w_{jk}(n_0 - 1)) \quad (5)$$

$$w_{ij}(n_0 + 1) = w_{ij}(n_0) + \eta \sum_{p_2=1}^{p} \delta_{ij}^{p_1} x_i^{p_1} + \alpha(w_{ij}(n_0) - w_{ij}(n_0 - 1)) \quad (6)$$

where n_0 is iteration times .

(7) Calculates x_j, y_k and E_{total} by new weights, where $E_{total} = \sum_{p_1=1}^{p}\sum_{i=0}^{m-1}(t_k^{p_1} - y_k^{p_1})$. In the light of requirement, if $|t_k^{p_1} - y_k^{p_1}|<\varepsilon$ is satisfied for every p_1 and k, learnig stops, where ε is a defined decimal and bigger than 0. Otherwise, goes to step (2) repeatedly to modify weights until $|t_k^{p_1} - y_k^{p_1}|<\varepsilon$ is satisfied.

(8) According to the stable weight acquired by training, classifies the sample and outputs classification results .

2 Design of the B-P Network Parameters

2.1 Design of input and output layer

According to the demand for evaluation of coal reserve assets, their categories are determined as m=5. So output layer is defined as 5 neurons. If $x^{p_1} \in j$th category, where x^{p_1} belongs to the training sample set, it is required that the output is $y=(0,0,1,0,0)^T$, that is, the jth output is 1 and the other outputs are 0. Therefore, for an n dimension input x, $x \in R^n$, classification reflection from $x \in R^n \rightarrow y \in R^m$, satisfies the following:

$y_j=1$, x^{p_1} belongs to jth category;

$y_j=0$, x^{p_1} not belongs to jth category.

Based on the quantity of the main influencing factors for the value of coal reserve asset, the input neuron numbers is determined as n = 19, shown in Fig.1 .

2.2 Number of hidden layer

It has been proved that a three-layer B-P network can realize the reflection from arbitrary n dimension to m dimension[5] , so the number of hidden layers is defined as 1.

2.3 Determination of hidden layer's neurons[4]

The number n_1 of the hidden layer's neurons is determined by the following formulas, and the optimal number is decided by testing for many times.

(1) $k < \sum_{i=0}^{n} C(^{n_1}_{i})$, where k is the number of samples, n_1 is hidden neuron number, and n is input neuron number.

(2) $n_1=\sqrt{n+m} + \alpha$, where m is output neuron number, n is input neuron number, and α is a constant between 1~10.

(3) $n_1 = \log_n^2$, where n is the number of input neurons .

3 Determining Model for Sample Parameter Values

Because the evaluation indices of main influence factors for the value of coal reserve assets are different each other, and no factor index can be compared with others, it is necessary that each factor index is transformed the quantity in interval [0,1], that is x_i (i=1,2,⋯,n) $\in$ [0,1]. It is defined that the greater an indice value is, the more favorably it affects the value of coal reserve asset, otherwise the more unfavorably. For an arbitrary input sample $x^{p_1} \in R^n$, its components $x_1^{p_1}$, $x_2^{p_1}$, ⋯, $x_n^{p_1}$ are determined by the fuzzy membership functions correspondingly (omit).

Evaluation values for price relation of coal ranks are determined in table 1.

4 Application Example

At first, coal resources data from 77 mines are used for modeling and classification. The canonical cases of the classification results by the fuzzy clustering model are employed as training samples, which are data from 33 mines of all. The others are used for classification.

By choosing different initial values, neural network is trained. After output errors satisfy requirement, classifying for coal reserve assets of 47 mines starts, then stable classification result can be obtained. Now the results by neural network method are compared with the results by the fuzzy method. By contrasting both, analyzing qualitatively the resources conditions of the classification objects, and referring to the studying achievement of the synthetic evaluation and classification for all national mines(in Nov., 1991), reasonable class of coal reserve assets can be determined. Those mines whose classification results for coal reserve asset by both methods are different from reasonable class show in table 2.

Table 2 shows that there are only five mines whose asset classes determined by neural network method differ from their reasonable class in all classification objects. The ratio of making a mistake is 10.4%. The classification results are close to the reasonable class with some fluctuation, and have no great errors. If the reliability of contrasting class is considered, the classification results have more reliability. Therefore the classification results by neural network method are stable and reliable.

Table 1 Evaluation values for various ranks of coal

Coal species	Coking coal	Bituminous coal used in coking	1/3 coking coal	Gas and bituminous coal	Gas coal	Sub-bituminous coal	1/2 neutral viscidity
Evaluation values	1.0	0.96	0.94	0.92	0.83	0.80	0.80
Coal species	weak viscidity	non-viscidity coal	lean coal	anthracite coal	lean and meagre	meagre coal	brown coal
Evaluation values	0.80	0.80	0.80	0.80	0.78	0.76	0.66

Table 2 Contrast of classification results

Mine code name	Classification results by neural network method	Classification results by the fuzzy method	Reasonble class for coal resources asset
2	II	I(×)	II
3	II	I(×)	II
5	I	II(×)	I
10	I	II(×)	I
14	II(×)	I	I
16	III(×)	II(×)	I
35	IV(×)	III	III
40	II	III(×)	II
46	III	II(×)	III
48	IV(×)	III	III
56	II	III(×)	II
75	III(×)	IV	IV

5 Conclusion

The model makes up the defect of the fuzzy model. Tested by practice examples, its classification results are reliable and stable, and conform to reality.

On the basis of the given model and algorithm, a computer software is developed with Turbo C. After achieving stable weight data by learning, the neural network can be used for classifying coal reserve assets in any mine or district without training once again.

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