FANN-Based Surface Water Quality Evaluation Model and Its Application in the Shaoguan Area

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Abstract A fuzzy neural network model is proposed to evaluate water quality. The model contains two parts: first, fuzzy mathematics theory is used to standardize the samples; second, the RBF neural network and the BP neural network are used to train the standardized samples. The proposed model was applied to assess the water quality of 16 sections in 9 rivers in the Shaoguan area in 2005. The evaluation result was compared with that of the RBF neural network method and the reported results in the Shaoguan area in 2005. It indicated that the performance of the proposed fuzzy neural network model is practically feasible in the application of water quality assessment and its operation is simple.

Keywords fuzzy neural network; RBF neural networks; BP neural networks; water quality evaluation

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Introduction

Evaluation of water quality is an important monitoring project. At present, there are many mathematical models for assessing water quality, such as the worst factor method, the principle component analysis method, the integrated pollution index method, the fuzzy comprehensive evaluation method[1] and the gray clustering method. However, these traditional methods fail to solve the complicated nonlinear relationship between evaluation indicators and the grade of water quality. In the evaluation process, the utility function (white function in the gray system, membership function in fuzzy mathematics) and the weights need to be designed artificially, which limits the ability of the evaluation models and also affects reliability.

Artificial neural networks (ANNs) are self-organizing, self-teaching, nonlinear and can deal with systems which are difficult to describe with traditional mathematical models. ANNs have been widely applied to hydrology. Huang Wenrui and Simon Foo presented an application of the artificial neural network to assess salinity variation in the Apalachicola River[2]. Kuo Yiming, Liu Chenguang and Lin Kao-hung applied the ANN model to assess the variation of groundwater quality in an area with blackfoot disease in Taiwan[3]. Integrated water quality evaluation is based on environment quality standards. Liu Lian-fang applied the BP neural network to the water evaluation of Liao River[4]. Huang Shengwei applied adaptive variable step size BP network to evaluate water quality[5]. Luo Dinggui designed the RBF model of surface water environment quality assessment[6].

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The theory and method of the fuzzy recognition (FR) have been widely applied in scientific research and achieved many results. Ding Tao applied fuzzy pattern recognition to water quality assessment of the Qiantang River[7]. Along with the development of the theory of the ANNs and the FR, the two theories have already begun to be integrated with each other. On the one hand, ANNs can solve the complicated nonlinear relationship between the inputs and outputs. On the other hand, FR can reflect the fuzzy relationship between the inputs and outputs. Compared with the “hard” classification method, since FR is closer to the practice, combining the two methods would produce complementary effects. Chen Shouyu proposed the fuzzy artificial neural network recognition (FANNR) model and used it to evaluate the water quality of Tuo River[8]. The training results of the FANNR model were objective and could reflect practical water conditions.

In this study, two fuzzy neural network models have been taken to evaluate water quality. The model contains two parts: in the first part, fuzzy mathematics theory is used to standardize the samples; in the second part, the RBF neural network and the BP neural network are respectively used to train the standardized samples. The paper is divided as follows: Section 1 discusses the structure of the fuzzy artificial neural network-based water evaluation model; Section 2 applies the RBF fuzzy neural network model and the BP fuzzy neural network model to water quality evaluation of rivers in the Shaoguan area in 2005 and compares the performance of the two models; Section 3 contains the concluding remarks.

1 Fuzzy artificial neural network (FANN)-based water evaluation model

1.1 Standardization with fuzzy mathematics

Assume that the testing set is composed of n samples, which contains m evaluation indicators, and the testing evaluation indicator matrix is of the form:

\[ X_{\text{test}} = (x_{ij})_{mn} \] (1)

where \( x_{ij} \) is the measured value of the evaluation indicator \( i \) of the sample \( j \).

The \( m \) indicators are assessed based on the evaluation standard which divides the water quality into \( c \) category grades. The evaluation criteria are numerical interval types. We have taken the standard category value to form the standard evaluation indicator matrix which is given by the form:

\[ Y_{\text{soc}} = (y_{ih})_{mc} \] (2)

where \( h \) is the category grade number of the standard evaluation indicators, and \( 1 \leq h \leq c \); \( y_{ih} \) is the standard category value of grade \( h \) of the evaluation indicator \( i \).

The pollution degree of the surface water is a fuzzy conception and its change is continuous. In this study, the degree of surface water pollution is described with relative grade of membership. In the standard evaluation indicator matrix, the grade of membership of grade 1 of indicator \( i \) is 0 to the fuzzy conception of pollution degree \( \mathcal{A} \); the grade of membership of grade \( c \) of indicator \( i \) is 1 to the conception of pollution degree \( \mathcal{A} \) and the grade of membership \( s_{ih} \) between grade 1 and grade \( c \) can be given by Eq.(3):

\[ s_{ih} = (y_{ih} - y_{i1})/(y_{ic} - y_{i1}) \] (3)

In the testing evaluation indicator matrix, the grade of membership \( r_{ij} \) of indicator \( i \) to fuzzy set \( \mathcal{A} \), can be given by Eq.(4):

\[
\begin{cases} 
0, & x_i \leq y_{i1} \\
(x_j - y_{j1})/(y_{ic} - y_{j1}), & y_{i1} < x_j < y_{ic} \\
1, & x_j \geq y_{ic}
\end{cases}
\] (4)

The grade of membership \( r_{ij} \) of indicator \( i \) to fuzzy set \( \mathcal{A} \), can be given by Eq.(5).

\[
\begin{cases} 
0, & x_j \geq y_{ic} \\
(x_i - y_{i1})/(y_{ic} - y_{i1}), & y_{ic} < x_i < y_{j1} \\
1, & x_i \leq y_{i1}
\end{cases}
\] (5)

The testing evaluation indicator matrix \( X_{\text{test}} \) and standard evaluation indicator matrix \( Y_{\text{soc}} \) have been converted to the relative grade of membership of the testing evaluation indicator matrix \( R_{\text{test}} \) and the relative grade of membership of standard evaluation indicator matrix \( S_{\text{soc}} \) with Eq.(3) to Eq.(5) respectively.

\[ R_{\text{test}} = (r_{ij})_{mn} \] (6)
where $h_{ij}$ means the grade of membership of the sample $j$ to grade $h$. The matrix $U_{cov}$ satisfies the restrictions:

$$
\sum_{j} h_{ij} = 1, 0 \leq h_{ij} \leq 1, \forall h, \forall j
$$

### 1.2 Constructing the model with the ANNs

In the first stage, samples have been standardized with fuzzy theory as described in Section 1.1. Next, the standardized samples were trained with the ANNs. The training results were used to determine the relative grade of membership of the category matrix $U_{cov}$. In this study, the RBF neural network and BP neural network were separately adopted in the training stage.

#### 1.2.1 BP neural network model

The typical three-layered BP neural network is comprised of multiple elements, which are also called nodes, and connection pathways that link them. The nodes are processing elements of the network and are normally known as neurons, reflecting the fact that the neural network method model is based on the biological neural network of the human brain. A neuron receives an input signal, processes it, and then transmits an output signal to other interconnected neurons.

First, the output of the network will be computed. In the hidden and output layers, the net input to unit $i$ is of the form:

$$
S_i = \sum_{j=1}^{k} w_{ji} y_j + \theta_i
$$

where $w_{ji} = (w_{i1}, w_{i2}, \cdots, w_{ik})$ is the weight vector of unit $i$, $y_j$ is the output from unit $j$, and $\theta_i$ is the bias of unit $i$. This weighted sum $S_i$, which is called the incoming signal of unit $i$, is then passed through a nonlinear transfer function ($f$) to yield the estimates $\hat{y}_i$ for unit $i$.

Several types of transfer functions are used; however, the most frequently used is the sigmoid function. This transfer function is usually a steadily increasing S-shaped curve. The sigmoid function is continuous, differentiable everywhere, and monotonically increasing. In this study, two S-shaped transfer functions in a MATLAB neural network toolbox were used: the tan-sig function and logsig function. The two functions are of the form:

$$
tansig(n) = \frac{2}{(1 + e^{-2n})} - 1
$$

$$
\text{logsig}(n) = \frac{1}{1/(1 + e^{-n})}
$$

These accumulated inputs are then transformed to the neuron output. This output is generally distributed to various connection pathways to provide inputs to the other neurons; each of these connection pathways transmits the full output of the contributing neuron.

Second, the error between the real output and the expected output will be computed. If the expected error is not satisfied, the precision, weights and biases will be adjusted according to the error.

Two steps constitute the one-time iteration. The iteration will be repeated until the error reaches the required precision or the predetermined training epochs. The adjusting process of the weights and the biases is called training. In this study, a momentum back propagation (MOBP) algorithm was used. The training function of the MOBP in the Matlab neural network toolbox is the traingdm function.

#### 1.2.2 RBF neural network model

The radial basis function (RBF) neural network can be described as a three-layer feed forward structure. It consists of three layers: the input layer, the hidden layer and the output layer. The input layer does not process the information; it only distributes the input vectors to the hidden layer. The hidden layer consists of a number of RBF units ($n_h$) and bias ($b_h$). Each hidden layer unit represents a single radial basis function with associated center position and width. Each neuron on the hidden layer employs a radial basis function as nonlinear transfer function to operate on the input data. The most frequently used RBF is the Gaussian function, which is characterized by a center ($c_j$) and a width ($r_j$). An RBF functions by measuring the Euclidean distance between input vector ($x$) and the radial basis function center ($c_j$) and performs the nonlinear transformation with the Gaussian RBF function.
in the hidden layer as given below:

\[ h_j(x) = \exp(-\|x - c_j\| / r_j^2) \]  

(12)

where \( h_j \) is the notation for the output of the \( j \)th RBF unit; and \( c_j \) and \( r_j \) are the center and the width for the \( j \)th RBF, respectively. The operation of the output layer is linear, which is given in the following equation:

\[ y_k(x) = \sum_{j=1}^{n_h} w_{kj} h_j(x) + b_k \]  

(13)

where \( y_k \) is the \( k \)th output unit for the input vector \( x \); \( w_{kj} \) is the weight connection between the \( k \)th output unit and the \( j \)th hidden layer unit and \( b_k \) is the bias.

From the above two equations, one can see that designing an RBF neural network involves the selection of centers, a number of hidden layer units, width and weights. In the MATLAB neural network toolbox, the RBF network design function is a newrb function, which can determine the number of the unit in the hidden layer automatically. The transfer function in the hidden layer is just the Gaussian function and the design function can also adjust the weights and biases.

### 1.3 Generation of the training set

The water quality is divided into five grades according to the Surface Water Environmental Quality Standard (GB3838-2002) issued by the government of China. The values of the criteria have been taken as the standard evaluation indicator values. Fuzzy neural networks have been trained with relative grade of membership of standard evaluation indicator matrix as inputs and the corresponding relative grade of membership of the category matrix as target outputs.

To increase the precision, a linear interpolation method was used for the standard evaluation indicator matrix to increase the number of the training samples. The process is as follows: training samples between all grades of the standard evaluation criteria are generated by the random uniform distribution method with the rand function in MATLAB. 500 samples are generated between grade 1 and grade 2, and the case is the same between the other grades. As a result, 2000 training samples have been generated. The standard target outputs of the five grades are (1, 0, 0, 0, 0), (0, 1, 0, 0, 0), (0, 0, 1, 0, 0), (0, 0, 0, 1, 0) and (0, 0, 0, 0, 1) respectively. Target outputs of the generated training samples are determined by the corresponding interpolation proportion. Table 1 shows the standard relative grades of membership of the training samples and the corresponding target outputs.

| Category | Standard relative grade of membership of training samples (generated by the \( S \) matrix) | Corresponding target outputs |
|----------|---------------------------------------------------------------------------------|-------------------------------|
| Grade 1  | \( s_{11}, \ldots, s_{1m} \)                                                      | 1 0 0 0 0                     |
| \( a(1)=\text{rand}(1) \) interpolation \( (1-a(1)) s_{11} + a(1) s_{12} \)      | \( (1-a(1)) s_{11} + a(1) s_{12} \)                                      |
| \( a(2)=\text{rand}(1) \) interpolation \( (1-a(2)) s_{11} + a(2) s_{12} \)      | \( (1-a(2)) s_{11} + a(2) s_{12} \)                                      |
|          | \( \ldots \)                                                                     | \( \ldots \)                 |
| Grade 2  | \( s_{12}, \ldots, s_{1m} \)                                                      | 0 1 0 0 0                     |
|          | \( \ldots \)                                                                     | \( \ldots \)                 |
| Grade c  | \( s_{1c}, \ldots, s_{m} \)                                                      | 0 0 0 0 1                     |

### 1.4 Determination of water quality

The grade of the testing water samples was determined by the grade eigenvalue method. The integrated evaluation matrix of the testing set was given by the following formula:

\[ H = \text{Grade} \times U_{\text{cst}} = (1, 2, \ldots, c) \times U_{\text{cst}} = (H_1, H_2, \ldots, H_c) \]  

(14)

where \( H_j (j=1, 2, \ldots, n) \) is the integrated evaluation value of the testing sample \( j \); \( \text{Grade} = (1, 2, \ldots, c) \); and \( U_{\text{cst}} \) is the training output of the testing set. The evaluation rule is that the testing sample \( j \) will belong to grade \( c \) if the inequation \( c-1 < H_j \leq c \) holds.

### 2 Application in the Shaoguan area

The Peal River Delta has for the recent two decades been the locomotive in the development of China’s economy. However, as the water source of
In this study, evaluation of 16 sections in 9 rivers in the Shaoguan area in 2005 was made and the main seven evaluation indicators chosen. The indicators are ammonium nitrogen (NH$_3$-NH$_4$), Hg, cadmium, Cr$^{6+}$, lead, volatility phenol and oils. The evaluation criteria and testing samples in the area are shown in Table 2 and Table 4, respectively. The evaluation criteria after standardization with fuzzy mathematics are shown in Table 3.

### 2.1 Evaluation standard and samples

In this study, evaluation of 16 sections in 9 rivers in the Shaoguan area in 2005 was made and the main seven evaluation indicators chosen. The indicators are ammonium nitrogen (NH$_3$-NH$_4$), Hg, cadmium, Cr$^{6+}$, lead, volatility phenol and oils. The evaluation criteria and testing samples in the area are shown in Table 2 and Table 4, respectively. The evaluation criteria after standardization with fuzzy mathematics are shown in Table 3.

### 2.2 Results and comparison

Testing samples in Table 4 were trained with the RBF fuzzy artificial neural network (RBFFANN) model described in Section 1. Because the training process is random, the network was trained 20 times. The prestd function in MATLAB was adopted to preprocess the training and testing samples which were standardized by Eqs.(3)-(5). The prestd function in MATLAB preprocesses the data so that the mean is 0 and the standard deviation is 1. For the input vector $p$, the algorithm of the prestd function is described as follows

$$p_n = (p - p_{mean}) / p_{std}$$

where the $p_{mean}$ is the mean for the vector $p$, the $p_{std}$ is the standard deviation for the vector $p$ and the $p_n$ is the normalized input vector.

Moreover, a comparison of training results of the networks not preprocessed with the prestd function was done in this study. Table 5 shows the time during
which each section belonged to a certain grade in training 20 times.

In the training process of the RBF fuzzy neural network, training error (here, the training error is the mean square error) was set as 0.001. The RBF network design function is the newrb function introduced in Section 1.2. The model which was preprocessed by the prestd function reached the goal in 41 epochs on average, and those which had no preprocessing of the prestd function reached the goal in 57 epochs on average. Table 5 shows the evaluation results of the 16 sections.

Samples in Table 4 have been trained with the BP fuzzy neural network as comparison. The training function is traingdm. The number of input neurons is 7, of hidden neurons is 8 and of output neurons is 5. The transmit functions in the two layers are tansig and logsig, respectively. The goal mean square error of the training is still 0.001. The maximum training epoch is 5,000 epochs. The training results of the BP fuzzy neural networks were compared. Results in Table 6 show that training samples preprocessed by the prestd function reach the required precision within 5,000 epochs, but those not preprocessed by the prestd

| Rivers          | Sections                        | NH$_4$-N | Hg     | Cd     | Cr$^{6+}$ | Lead | Volatile phenol oils |
|-----------------|---------------------------------|----------|--------|--------|-----------|------|----------------------|
| North River     | Mengzhou Dam                    | 0.317    | 0.000 06 | 0.008 6 | 0.012     | 0.017 | 0.002 0              |
|                 | High Bridge                     | 0.196    | 0.000 04 | 0.007 6 | 0.013     | 0.017 | 0.002 0              |
|                 | Baisha                          | 0.324    | 0.000 04 | 0.016 1 | 0.006     | 0.012 | 0.002 0              |
|                 | Long Dam                        | 0.153    | 0.000 05 | 0.002 0 | 0.016 0   | 0.011 | 0.002 0              |
| Zhen River      | Qu River Bridge                 | 0.162    | 0.000 05 | 0.003 0 | 0.014     | 0.012 | 0.002 0              |
|                 | Gushi                           | 0.392    | 0.000 04 | 0.002 0 | 0.028     | 0.005 | 0.002 0              |
|                 | Pingshi                         | 0.211    | 0.000 05 | 0.001 8 | 0.007 0   | 0.005 | 0.002 0              |
| Wu River        | Wu River Bridge                 | 0.333    | 0.000 06 | 0.001 8 | 0.009 0   | 0.005 | 0.002 0              |
|                 | Wu Mountain Substation          | 0.119    | 0.000 07 | 0.003 2 | 0.006 0   | 0.016 | 0.002 0              |
|                 | Mo River                        | 0.106    | 0.000 04 | 0.002 0 | 0.015 0   | 0.014 | 0.003 2              |
|                 | Mo River Exit                   | 0.182    | 0.000 01 | 0.002 0 | 0.011 0   | 0.012 | 0.002 0              |
| Jin River       | Danxia Mountain                 | 0.047    | 0.000 09 | 0.002 0 | 0.006 0   | 0.011 | 0.005 3              |
|                 | Stibium Factory Downstream      | 0.553    | 0.000 04 | 0.002 0 | 0.004 0   | 0.001 | 0.002 0              |
| South River     | Longgui River Exit              | 1.938    | 0.000 04 | 0.113 0 | 0.005 0   | 0.471 | 0.005 2              |
|                 | Maba River                      | 0.292    | 0.000 01 | 0.002 5 | 0.009 0   | 0.004 | 0.002 0              |
| Wu River        | Guandu                          | 0.397    | 0.000 02 | 0.001 3 | 0.030 0   | 0.005 | 0.0010               |
|                 | Tanshi                          |          |         |         |           |      | 0.012               |

| Tables 4 and 5 | Results of RBF fuzzy artificial neural network |
|-----------------|-----------------------------------------------|
| Rivers          | Sections                                      |                |        |        |        |                      |
|                 |                                               | Not preprocessed by prestd | | | | | Preprocessed by prestd |
|                 |                                               | 1 2 3 4 5       | 1 2 3 4 5 | Grade |
| North River     | Mengzhou Dam                                  | 18 2           | 9 11 4-5 |
|                 | High Bridge                                   | 18 2           | 9 11 4-5 |
|                 | Baisha                                        | 18 2           | 9 11 4-5 |
|                 | Long Dam                                      | 20 20          | 2       |
| Zhen River      | Qu River Bridge                                | 13 7           | 19 1 3   |
|                 | Gushi                                          | 20 10          | 2-3      |
|                 | Pingshi                                       | 20 20          | 2       |
| Wu River        | Wu River Bridge                                | 20 17 3       | 2-3      |
|                 | Wu River Bridge                                | 2 18 4 16     | 3-4      |
|                 | Mo River                                      | 19 1 20        | 2       |
|                 | Danxia Mountain                                | 14 6 20        | 2-3      |
| South River     | Longgui River Exit                             | 20 14 6       | 2-3      |
|                 | Stibium Factory Downstream                    |                |          |
|                 | Stibium Factory Downstream                    | 20 14 6       | 2-3      |
| Maba River      | Maba River Exit                               | 18 2 9 11 4-5 |
| Weng River      | Guandu                                        | 18 2 20        | 3       |
| Xinfeng River   | Tanshi                                        | 9 11 10 10     | 3-4      |
| Training precision | Training error                                | <0.001 0      |
|                 | Training epochs                               | 57 41          |

Table 5 | Rivers | Sections | Not preprocessed by prestd | | | | | Preprocessed by prestd | | |
|--------|---------|---------------------------------|---|---|---|---|---|---|---|---|---|
| North River | Mengzhou Dam | 18 2 9 11 4-5 | | | | | | | | |
| North River | High Bridge | 18 2 9 11 4-5 | | | | | | | | |
| North River | Baisha | 18 2 9 11 4-5 | | | | | | | | |
| North River | Long Dam | 20 20 2 | | | | | | | | |
| Zhen River | Qu River Bridge | 13 7 19 1 3 | | | | | | | | |
| Zhen River | Gushi | 20 10 2-3 | | | | | | | | |
| Zhen River | Pingshi | 20 20 2 | | | | | | | | |
| Wu River | Wu River Bridge | 20 17 3 2-3 | | | | | | | | |
| Wu River | Wu River Bridge | 2 18 4 16 3-4 | | | | | | | | |
| Wu River | Mo River Exit | 19 1 20 2 | | | | | | | | |
| Wu River | Danxia Mountain | 14 6 20 2-3 | | | | | | | | |
| South River | Longgui River Exit | 20 14 6 2-3 | | | | | | | | |
| South River | Stibium Factory Downstream | | | | | | | | | |
| South River | Stibium Factory Downstream | | | | | | | | | |
| Maba River | Maba River Exit | 18 2 9 11 4-5 | | | | | | | | |
| Weng River | Guandu | 18 2 20 3 | | | | | | | | |
| Xinfeng River | Tanshi | 9 11 10 10 3-4 | | | | | | | | |
| Training precision | Training error | <0.001 0 | | | | | | | | |
| Training precision | Training epochs | 57 41 | | | | | | | | |
Table 6  Results of BP fuzzy artificial neural network

| Rivers         | Sections             | Not preprocessed by prestd | Preprocessed by prestd |
|---------------|----------------------|----------------------------|------------------------|
|               |                      | No.1 Grade No.2 Grade No.3 Grade | No.1 Grade No.2 Grade No.3 Grade |
| North River   | Mengzhou Dam         | 4 3 3                       | 3 3 3                  |
|               | High Bridge          | 3 2 3                       | 3 2 3                  |
|               | Baisha               | 4 3 3                       | 3 3 3                  |
|               | Long Dam             | 2 2 2                       | 2 2 2                  |
| Zhen River    | Qu River Bridge      | 2 2 2                       | 2 2 2                  |
|               | Gushi                | 2 2 2                       | 2 2 2                  |
|               | Pingshi              | 2 2 2                       | 2 2 2                  |
| Wu River      | Chang Mountain Substation | 2 2 2                  | 2 2 2                  |
|               | Wu River Bridge      | 2 2 2                       | 2 2 2                  |
| Mo River      | Mo River Exit        | 2 2 2                       | 2 2 2                  |
| Jin River     | Danxia Mountain      | 2 2 2                       | 2 2 2                  |
| South River   | Stibium Factory Downstream | 2 2 2                  | 2 2 2                  |
|               | Longgui River Exit   | 2 2 2                       | 2 2 2                  |
| Maba River    | Maba River Exit      | 4 3 4                       | 5 4 4                  |
| Weng River    | Guandu               | 2 2 2                       | 2 2 2                  |
| Xinfeng River | Tanshi               | 2 2 2                       | 2 2 2                  |

Training function cannot reach the performance goal after the maximum epoch. Because the result of the BP network is random, each case has been trained 3 times.

Results of the RBF fuzzy artificial neural network (RBFFANN) were compared with that of the RBF neural network (RBFNN) method introduced in Reference [6] and the reported results in the Shaoguan area in 2005. Results are shown in Table 7.

Table 7  Results comparison of the three methods

| River         | Sections             | RBFFANN  | RBFNN  | Reality |
|---------------|----------------------|----------|--------|---------|
| North River   | Mengzhou Dam         | 4-5      | 4      | 5       |
|               | High Bridge          | 4-5      | 3      | 5       |
|               | Baisha               | 4-5      | 4      | 5       |
|               | Long Dam             | 2        | 2      | 3       |
| Zhen River    | Qu River Bridge      | 3        | 2      | 3       |
|               | Gushi                | 2-3      | 3      | 3       |
|               | Pingshi              | 2        | 3      | 2       |
| Wu River      | Chang Mountain Substation | 2-3      | 4      | 3       |
|               | Wu River Bridge      | 3-4      | 2-3    | 3       |
| Mo River      | Mo River Exit        | 2        | 3      | 3       |
| Jin river     | Danxia Mountain      | 2-3      | 2-3    | 3       |
| South River   | Stibium Factory Downstream | 2-3      | 3-4    | 4       |
|               | Longgui River Exit   | 3-4      | 4      | 4       |
| Maba River    | Maba River Exit      | 4-5      | 4      | 5       |
| Weng River    | Guandu               | 3        | 3-4    | 2       |
| Xinfeng River | Tanshi               | 3-4      | 3-4    | 2       |
3 Conclusions

This study combines fuzzy mathematics theory and artificial neural networks to propose the fuzzy artificial neural network model and applies the model to water quality assessment of 16 sections in 9 rivers in the Shaoguan area in 2005.

The evaluation results show that water quality in the North River and Maba River is the worst and the quality grade is between 4 and 5. Water quality in the other rivers is between grade 2 and grade 3. Table 2 and Table 4 show that in the North River, only the value of the Cd is bad, but the bad/poor evaluation result is the same as that of the Maba River. This shows that that some evaluation indicators in the Surface Water Environment Quality Standard (GB3838-2002) have the same limit value in different grades. For example, from grade 2 to grade 4, the limit values of the Cd are all 0.05. Table 3 shows that after being standardized, the limit value of grade 2 to grade 4 of the Cd are much higher than almost other evaluation indicators; if the Cd value of the sample is bad, the evaluation result thus will be bad.

From the comparison of Table 5 and Table 6, we can see that the RBF fuzzy neural network outperforms. With the same training precision, the training speed of the RBF fuzzy neural network is much higher than that of the BP fuzzy neural network. For the network not preprocessed with the prestd function, the RBF fuzzy neural network reached the goal training error of 0.001 in 57 epochs on average; but as for the BP fuzzy neural network, the training error was still higher than 0.001 after 5 000 training epochs. For the network preprocessed with the prestd function, the RBF fuzzy neural network reached the goal training error of 0.001 in 41 epochs; the BP fuzzy neural network reached the goal training error in thousands of epochs. The performance of the RBF fuzzy neural network is superior to the BP fuzzy neural network.

Results of the RBF fuzzy artificial neural network have been compared with that of the RBF neural network method introduced in Reference [6] and the reported results in the Shaoguan area in 2005. Table 7 shows the comparison. The conclusion is that the fuzzy neural network is feasible in practical water quality assessment applications and its operation is simple.

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