Surface Water Quality Evaluation Using BP and RBF Neural Network

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***Abstract*—It is very important to evaluate water quality in environment protection. Water environment is a complicated system, traditional methods cannot meet the demands of water environment protection. In view of the deficiency of the traditional methods, a BP neural network model and a RBF neural network model are proposed to evaluate water quality. The proposed model was applied to evaluate the water quality of 10 sections in Suzhou River. The evaluation result was compared with that of the RBF neural network method and the reported results in Suzhou river. It indicated that the performance of proposed neural network model is practically feasible in the application of water quality assessment and its operation is simple.**

***Index Terms*—water quality;RBF neural network; BP neural network; evaluation**

I. Introduction

Water quality assessment is an important monitoring project. At present, there are many methods to evaluate the water quality ,such as Fuzzy Comprehensive Evaluation, Unascertained measure, Gray correlation analysis method, gray clustering method, integrated pollution index method[1][2]. Every method has his own characters. These traditional methods can not solve the complicated nonlinear relationship between evaluations indicators and the grade of water quality. Because there are many factors affecting the water quality in river, and the factors is nonlinear relations with water quality. Traditional assessment can not meet the demands for evaluating precision, while artificial Neural networks are loosely based on the neural structure of the brain which provide the ability to learn from the input data they are given and then apply this to unknown data, in effect they can generalize and associate unknown data.

Artificial neural networks(ANNs) are self-organizing ,self-teaching, nonlinear and can deal with the systems which are difficult to described with traditional methods[3][4][5]. In recent years, many researchers have been conducted on the water quality assessment. Liu Lianfang applied BP neural network to the water evaluation of Liao River.Yang Meini allpied Fuzzy artificial neural network to the surface water evaluation in the Shaoguan area. Luo Dinggui designed the RBF model of surface water environment quality assessment [5]. Matlab is mathematical software with high-level numerical computation and data visualization capability. It can provide users with neural network design and evaluation and enable them to work on at greater convenience..

II. Constructing the Model with ANNs

A. BP neural network model

After the first simple neural network developed by McCulloch and Pitts (1943) , many types of ANN have been proposed. The neural network model with multi-hierarchic structure which is based on back-propagation (BP) arithmetic, the most widely used ANN in hydrologic modeling, is used in this study. The BP network has all the functions of the neural network and its unique advantages such as the good mapping ability of processing the rainfall-runoff partitioning with more flexibility. In addition, its network model contains a highly parallel inter-connection structure, fast self-learning and handling ability of self-adaptation, which provide foundations for the application in hydrology, especially in rainfall-runoff modeling using the incomplete material. Therefore, the BP neural network is a popular choice in the field of hydrology with various complex physical processes.

In recent years, neural network has been widely applied to the teaching evaluation , in which BP network is commonly used . The model created in this paper is a BP neural network with three-layer network (Figure1) .

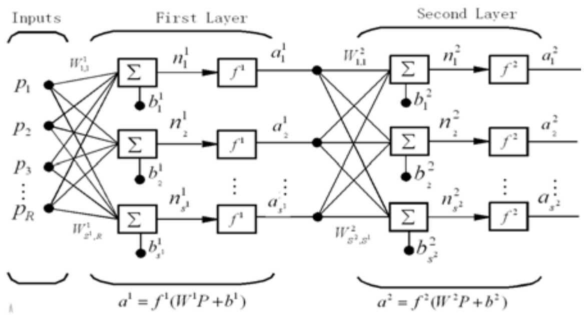

Figure 1. Three-layer BP network structure

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In the Figure 1, p is input of neuron. Each layer has its own weight matrix $\vec{W}$, its bias vector $\vec{b}$, a net input vector $\vec{n}$, and an output vector $\vec{a}$. $\vec{W}$ is an $S \times R$ matrix, and $\vec{a}$ and $\vec{b}$ are vectors of length S respectively. The superscripts of symbols identify the layers. Also shown in Figure 1 are R input, S^1 neurons in the first layer, and S^2 neurons in the second layer. Different layers can have different numbers of neurons. The outputs of layers one and two are the inputs for layers two and three. Thus layer 2 can be viewed as a one-layer network with $R = S^1$ inputs, $S = S^2$ neurons, and an $S^1 \times S^2$ weight matrix $\vec{W}^1$. The input of layer 2 is $\vec{a}^1$, and the output is $\vec{a}^2$. The other layer also can be drawn using same abbreviated notation.

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:

$$s_i = \sum w_{ji} y_i + \theta_i \tag{1}$$

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 tansig function and logsig function. The two functions are of the form:

$$\tan sig(n) = \frac{2}{1 + e^{-2n}} - 1 \tag{2}$$

$$\tan sig(n) = \frac{1}{1 + e^{-n}} \tag{3}$$

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.

The process can be described as Figure 2.

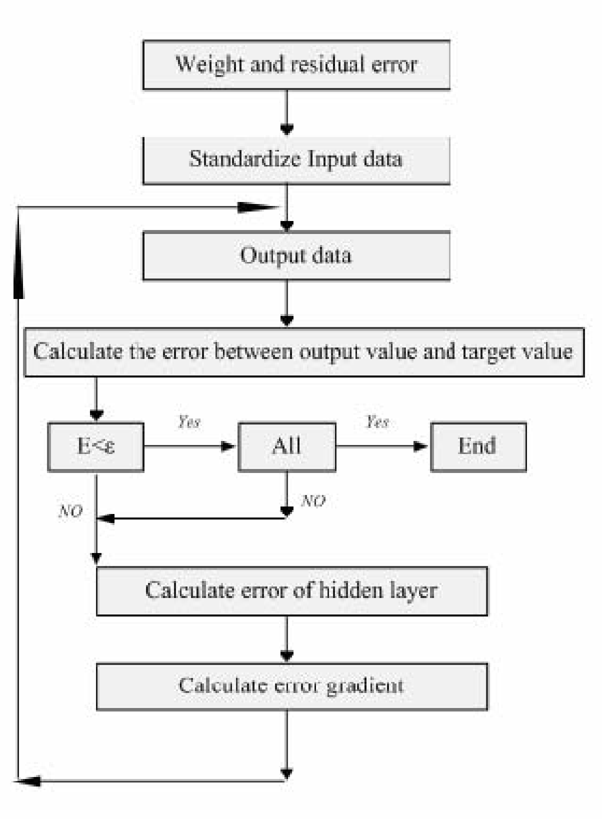


Figure 2. Flowchart of BP neural networks algorithm

B. RBF NEURAL NETWORK

A radial basis function (RBF) is a real-valued function whose value depends only on the distance from the origin, so that $\phi(x) = \phi(\| x \|)$; or alternatively on the distance from some other point *c*, called a *center*, so that $\phi(x, c) = \phi(\| x - c \|)$. Any function φ that satisfies the property $\phi(x) = \phi(\| x \|)$ is a radial function. The norm is usually Euclidean distance.

Radial basis functions are typically used to build up function approximations of the form

$$y(x) = \sum_{i=1}^{N} w_i \phi(\| x - c_i \|) \tag{4}$$

where the approximating function $y(\boldsymbol{x})$ is represented as a sum of *N* radial basis functions, each associated with a different center $\boldsymbol{c}_i$, and weighted by an appropriate coefficient w_i. Approximation schemes of this kind have been particularly used in time series prediction and control of nonlinear systems exhibiting sufficiently simple chaotic behaviour, 3D reconstruction in computer graphics (for ex. hierarchical RBF) .

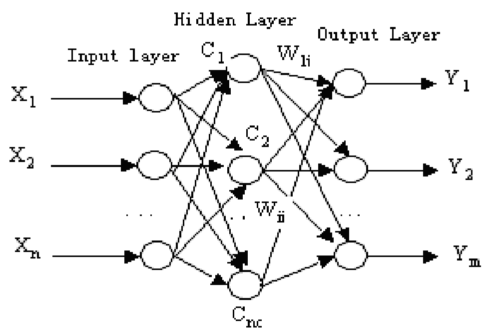


Figure 3. RBF neural network Structure

There are three learning parameters:: center of RBF C_K 、 σ_K W_K. The process of algorithm as followings:

(1) choosing one series C_K from input matrix;

(2) Calculating variance

$$\sigma = \frac{d_{\max}}{K} \tag{5}$$

Where $d_{\max}$ is the maximum distance, K is the number of C_K;

(3) Calculating $\hat{y}_i(n)$ according to $x(n)$

$$\hat{y}_i(n) = \sum_{k=1}^{M} W_K \phi[x(n), C_K, \sigma_K] \tag{6}$$

(4) update RBF parameters

$$W(n+1) = W(n) + \mu_w e(n)\phi(n) \tag{4}$$

$$C_K(n+1) = C_K(n) + \mu_C \frac{e(n)W_K(n)}{\sigma_K{}^2(n)} * \phi[x(n), C_K(n), \sigma_K][x(n) - C_K(n)] \tag{7}$$

$$\sigma_K(n+1) = \sigma_K(n) + \mu_\sigma \frac{e(n)W_K(n)}{\sigma_K{}^2(n)} \phi[x(n), C_K(n), \sigma_K]\|[x(n) - C_K(n)]\|^2 \tag{8}$$

$$\phi(n) = \begin{Bmatrix} \phi[x(n), c_1(n), \sigma_1], \phi[x(n), c_2(n), \sigma_2], \\ \dots, \phi[x(n), c_N(n), \sigma_N] \end{Bmatrix}^T \tag{9}$$

$$e(n) = \hat{y}_i(n) - y_d(n) \tag{10}$$

$y_d(n)$ is the expired output; μ_N, μ_C, μ_σ are the echoes of three parameters.

(5) If network convergence, stop the calculation, otherwise go to process (3) . The detail procedures can be seen in Figure.4.

III. APPLICATION

A. Study area

Suzhou is a famous city with much water, in which river port interlocks and numerously lake. water surface in whole city approximately is 3607 square kilometers, which approximately composes the total area 42.52%. The urban district water surface is approximately 24 square kilometers, composing the urban district area 20.15%. Suzhou altogether has more than 4000 bigger lakelet, the big lake swings has 87; Altogether has size rivers 20,000, total length 1457km. Outside the moat the Suzhou old city area circle will become a relatively independent region, spreads across the river course has formed “three horizontal three straight link” the urban river course network of rivers and lakes system with the city. The rivers height is equally 0.8-1.3m (the Woosung elevation) , the water depth is equally 3 meters, the gradient is zero nearly. The river water excretes weakly, therefore the fluent speed of flow is very small, mean velocity of stream is 0.05m/s~0.1m/s.

B. Generation of training set

Water quality is divided into five grades according to the Surface Water Environmental Quality Standard (GB3838-2002) issued by the government of China [7]. Table I shows the Surface Water Environmental Quality Standard BP neural networks have been trained with grade of standard evaluation indicator matrix as input and the grade of category matrix as target outputs[8][9].

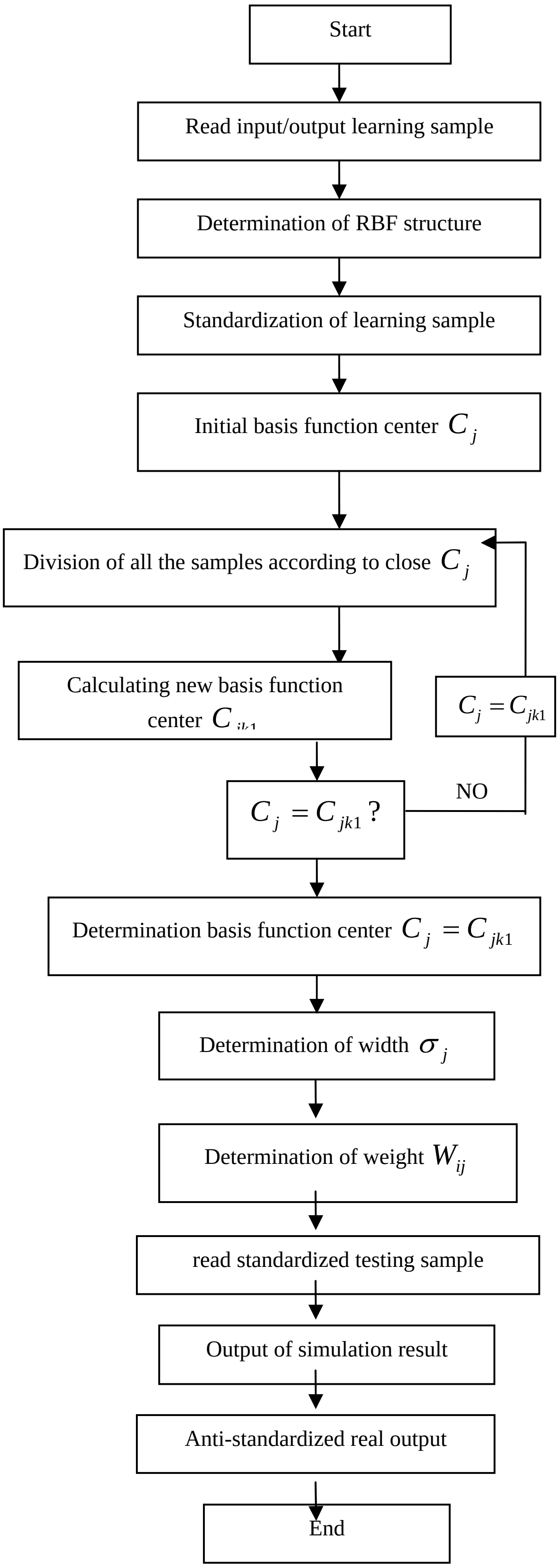


Figure 4. Flow chart of RBF neural network

TABLE I. SURFACE WATER ENVIRONMENTAL QUALITY STANDARD

Indicator j	I	II	III	IV	V
DO	>7.5	6.0	5.0	3.0	<2.0
BOD_5	<3.0	3.0	4.0	6.0	>10.0
COD_{cr}	<15.0	15.0	20.0	30.0	40.0
NH_3-N	<0.015	0.5	1.0	1.5	2.0
Phenol	0.002	0.002	0.005	0.01	0.1

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) ,(0,0,0,0,1) . The result of target outputs can be seen in Table II.

C. Pre-processing of data

Data pre-processing is an important initial work. The process includes training sample's size, criterion unitizing transforms (unification replacement) , the statistical property research, spatial information processing as well as singular value processing and so on. Before the data is processed, the data should bedivided into two groups: training sample and examining sample. There are several types of preprocessing methods. All the training data are rescaled to a specific range (e.g., [-1, 1] or [0, 1]) . However, the BP model is based on the gradient descent algorithm and the transfer function which determines the relationship between inputs and outputs of a node and a network has an asymptotic nature. When the extreme values of discharge are utilized, the gradient of the transfer function will approximate to zero, consequently, leading to slow the training down.

The next issue is the division of the data into the training and testing data set. The training data set is presented repeatedly to the network until the weight values are determined while the testing data set is used for the final evaluation of the BP model performance. Sometimes to overcome the problem of overfiting or to determine the stopping point of the training process, the validation set is also required. The testing data set is used for both validation and testing in this study. Although there are no general solutions to the selection of the training and testing set which may affect the performance of the BP model, both the training and testing sets representative of the evaluation system data should be carefully evaluated in the decision making

D. Water quality evaluation model

1) BP evaluation Model

(1) Neuron determination of input layer

According to the indicator system, the main index affecting teaching quality is 5 (Table I), so the number of input layer can be adopted as 5. The determination of input pattern is the key for the successful neural network model. If the input neurons are more, the structure of model is more complex and training period is long. Otherwise, it is difficult to get the nonlinear relationship.

(2) The number of hidden layers and nodes

ANNs perform complicated nonlinear mapping between input and output variables through the hidden nodes in the hidden layer. It can capture the pattern in the data. So the hidden layer and nodes play very important roles in the network architecture. Most studies indicate that a single hidden layer network tends to be used to the modeling problem and if the number of hidden nodes is enough, we can obtain any desired accuracy. However, other studies demonstrated the benefits of an ANN comprised of two hidden layers . In the recognizance of these studies, a single hidden layer is used in this study.

The number of hidden nodes has comparatively great difficulty in determining. The neuron selection in the hidden layer affects the precise calculation and learning efficiency for the whole BP network, up till now, there are still no unified ways to identify the number of the hidden layer neuron, which is at the stage of research and exploration. If a small number of the hidden layer neurons are chosen, the self-adaptability of the BP neural network will be reduced, thus the training results are not ideal. However, if the large number is chosen, it is generally believed that the time for network training will be greatly increased, and some meaningless information in training data will be remembered, thus it will reduce precise calculation in a sense. The most common way in determining the number of hidden nodes is by using experiments or by trial-and-error. Thus in this study the more appropriate number of the hidden layer neuron is fixed for six through testing and comparing. Therefore, the chosen configuration for the BP model is 5-8-5: five inputs, eight hidden neurons in one hidden layer and five outputs.

TABLE II. PERFORMANCE COMPARISON IN DIFFERENT TOPOLOGY OF BP NEURAL NETWORK

BP Neural Network	**Topology**	**Epochs**	**mse**
BP I	5-7-5	1871	0.00000997887
BP II	5-8-5	1434	0.00000993658
BPIII	5-9-5	2128	0.00000998447
BPIV	5-10-5	2066	0.00000994926
BP V	5-11-5	1652	0.0000099837

(3) Results

According to the BP network test (simulation identification), the water environmental quality on the 20 monitoring sections in Suzhou River are evaluated. The results are shown in Table II.

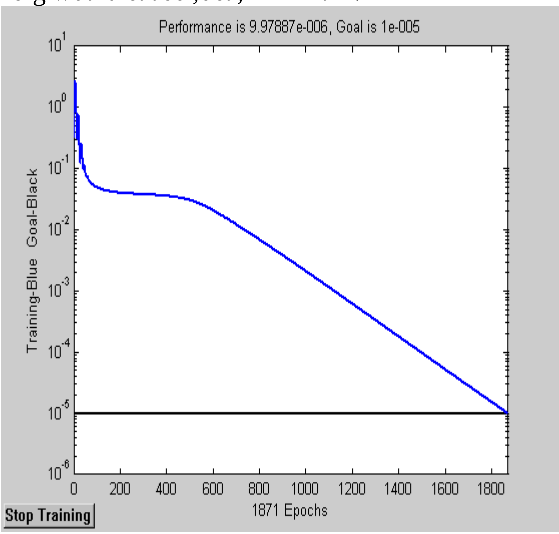
П) RBF neural network

(1) Creation of Rbf neural network

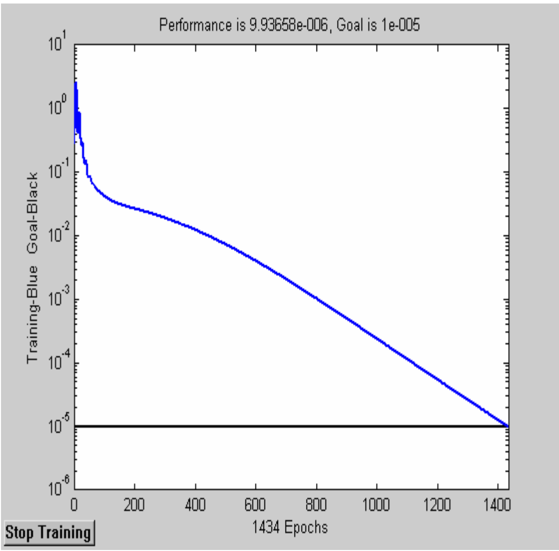
RBF network input layer neurons depends on the number of indicators of water quality evaluation. According to meaning of the questions identified as 5, the output layer neurons is set to 5, the use of MATLAB 6. 5 in the NEWRB functions to create the network, automatically determines the required hidden layer unit number.Hidden layer unit activation function for the RADBAS

(2) Training, testing and evaluation

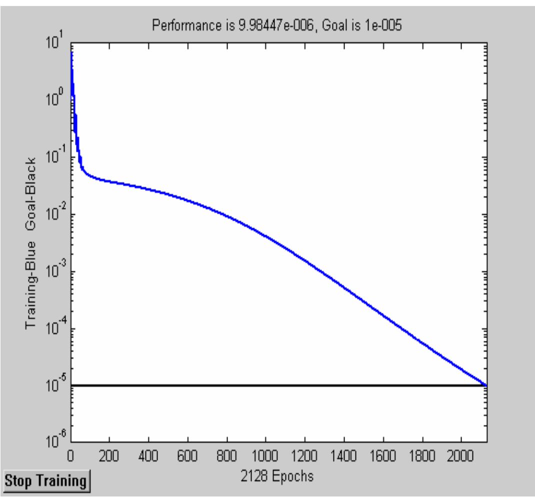
The process of creating RBF neural netwok is also a learning process. The important parameter is SPREAD. The parameter is the pace of expansion of radial basis function. Its value can not be too small and not too big, too small will affect the network’s convergence speed, too big would cause ;oca; minimum.



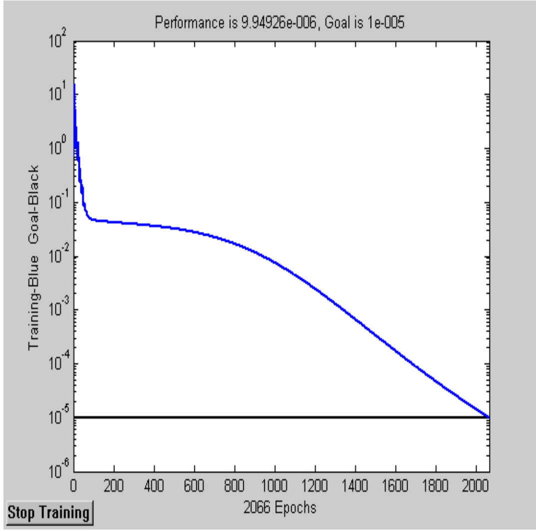
(a) 5-7-5



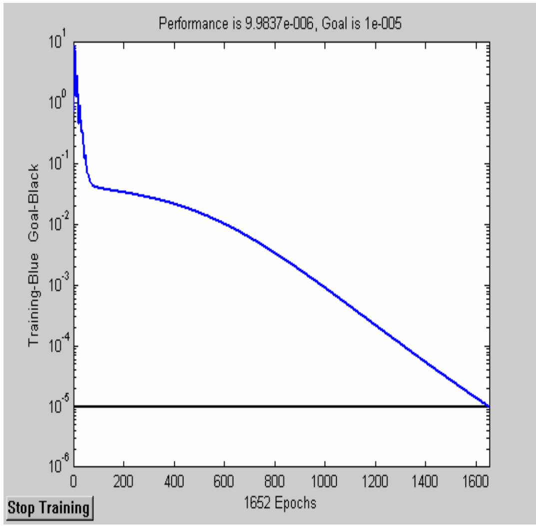
(b) 5-8-5



(c) 5-9-5



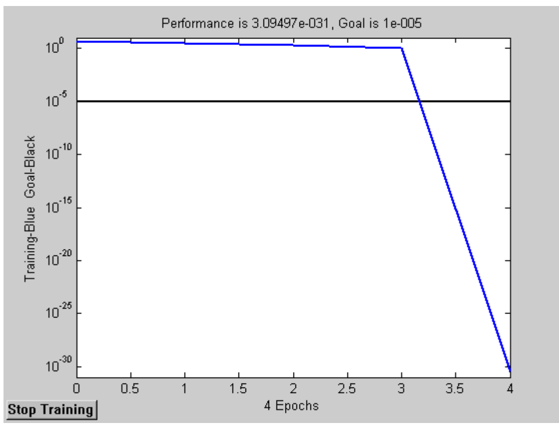
(d) 5-10-5



(e) 5-11-5

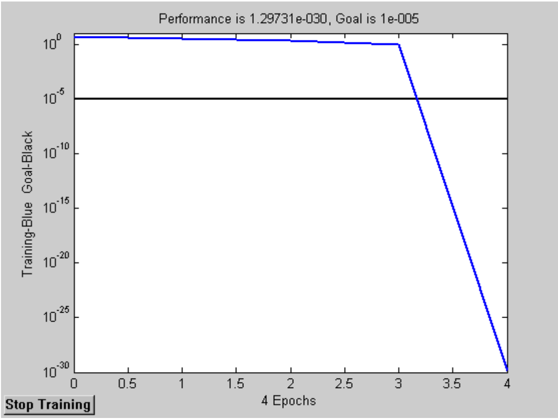
Figure 5. Relation of different topology with epochs

In the process, different SPREAD value is needed to detemine an optimal value. In this study, the value of SPREAD is 0.2, 0.25, 0.4, 0.45, 0.55,which is called RBF I, RBF II, RBF III, RBF IV, RBF V.



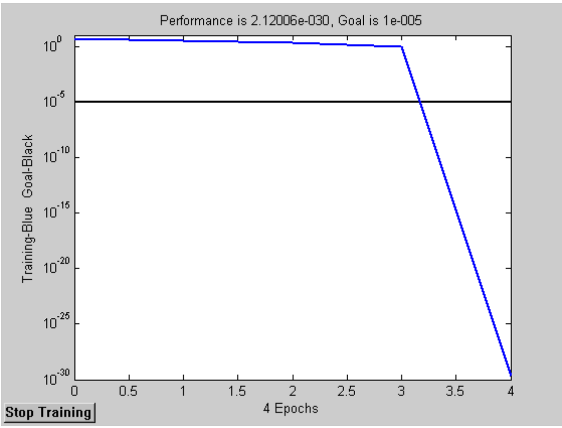
(a) spread is 0.2

After 4 epochs, network is convergence, the final square error E(g1) =mse_1=3.09497e-031



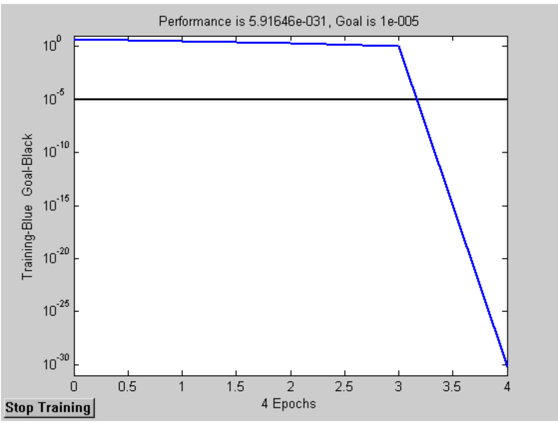
(b) spread is 0.25

After 4 epochs, network is convergence, the final square error E(g2) $=mse_{II}=1.29731e\text{-}030$



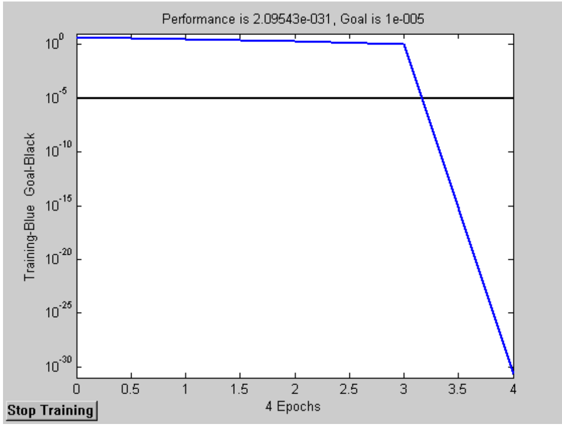
(c) spread is 0.4

After 4 epochs, network is convergence, the final square error E(g3) $=mse_{III}=2.12006e\text{-}030$



(d) spread is 0.45

After 4 epochs, network is convergence, the final square error E(g4) $=mse_{IV}=5.91646e\text{-}031$



(e) spread is 0.55

After 4 epochs, network is convergence, the final square error E(g5) $=mse_{V}=2.09543e\text{-}031$

Figure 6. Relation of different SPPREAD with epochs

TABLE III. PERFORMANCE COMPARISON IN DIFFERENT TOPOLOGY OF RBF NEURAL NETWORK

RBF Neural Network	Topology	Epochs	mse
RBF I	0.2	4	3.09497e-031
RBF II	0.25	4	1.29731e-030
RBF III	0.4	4	2.12006e-030
RBF IV	0.45	4	5.91646e-031
RBF V	0.55	4	2.09543e-031

Seen from Table III and IV, compared to other models, RBF V optimal network performance model, the model in the loop 4 times after the network convergence, the final mean square error of 2.09543e-031, for Table III, models in the minimum mean square error of the model, so this Suzhou Creek water quality evaluation should use RBF V Network

IV. CONCLUSIONS

This paper adopts the BP and RBF neural network to evaluate the water quality in Suzhou river. Some conclusions can be got by our research:

(1) BP and RBF neural network can be used to evaluate the water quality. The results are objective.

(2) The result of evaluation through BP neural network has high precision. RBF's convergence is fast than BP's

(3) The assessment result can provide reference to the water environment protection and plan kind of pagination.

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TABLE IV. EVALUATION RESULTS OF BP NEURAL NETWORK IN SUZHOU RIVER

Section	BP	RBF	Function zone
1	IV	IV	IV
2	IV	IV	IV
3	IV	IV	IV
4	V	IV	IV
5	IV	IV	IV
6	I	V	V
7	I	IV	V
8	IV	V	V
9	IV	IV	IV
10	IV	IV	IV