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Application of RBF and GRNN Neural Network Model in River Ecological Security Assessment—Taking the Middle and Small Rivers in Suzhou City as an Example

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Abstract: The analytic hierarchy process is used to construct the health evaluation index system and grading standard of small- and medium-sized rivers in the region. Based on the principles of RBF and GRNN neural network algorithms, the river health evaluation models of radial basis function neural network (RBF) and general regression neural network (GRNN) algorithms are constructed, respectively. The network training samples are constructed by the interpolation method. The standard value of river health classification evaluation is taken as the "prediction" sample to "predict". Then the results are applied as the division basis of the river health classification evaluation, which is to evaluate and analyze the health status of small and medium rivers in Suzhou Prefecture. The results indicate that: (1) the RBF and GRNN neural network models have exactly the same results in evaluating the health of small and medium rivers in the region, and are basically the same as the back propagation (BP) neural network evaluation results. RBF and GRNN neural network models have the advantages of fast convergence speed, high prediction accuracy, harder to fall into local minima, less adjustment parameters, and only one spread parameter, which can predict and evaluate the network faster, which is a large calculation advantage. (2) The health evaluation level of the main rivers in Suzhou Prefecture is from grades II to III, that is, between healthy and sub-healthy. This grade objectively reflects the health status of small- and medium-sized rivers in the region, which can provide a reference for the sustainable management of regional rivers and ecological environment construction.

Keywords: river ecological security assessment; radial basis neural network (RBF); generalized regression neural network (GRNN); Suzhou city

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1. Introduction

The concept of ecological security has not yet reached a consensus on the inadequacy of the concept of river ecological security. Scholars from different countries have expounded and interpreted its connotation from different aspects, and their research purposes and research backgrounds are different [1]. River ecological security can be understood as the river maintaining the integrity of its ecosystem structure, giving full play to its natural ecological functions, and providing corresponding social service functions when the river ecosystem is in a good state [2–4]. The characterization and evaluation technology of river ecological security status can not only be applied to the objective description and evaluation of river status, but also can effectively evaluate the effect of ecological restoration on damaged rivers, which is essential for the sustainable management of rivers and the construction of the regional ecological environment [5]. There are many methods of river ecological security evaluation, but from the evaluation principle, it can be mainly divided into prediction model method and multi-index method [6,7]. The multi-index method is a comprehensive evaluation of the characteristics of various aspects of a river. Its results are more comprehensive and objective, which is a development direction in the evaluation of river ecological security [4]. It is tough or inappropriate to establish a conventional mathematical model for the multi-index evaluation system. The model can only be established by means of methods such as artificial intelligence, fuzzy recognition, and knowledge engineering to deal with the comprehensive evaluation of the multi-index system [7]. Currently, artificial intelligence methods have become some of the most effective ways to establish and evaluate such complex systems, wherein an artificial neural network is one of the most widely used algorithms amongst these types of intelligent algorithm. With reference to the relevant literature [2,8], this paper first uses the analytic hierarchy process to design the river health level evaluation index system. Then, an intelligent evaluation model of river health is constructed by using radial basis function neural network (RBF) and generalized regression neural network (GRNN) with similar network structure, which takes the evaluation index system as the input data. This is quite an academic innovation in the industry. Due to their good approximation performance and generalization ability, they can be used for river ecological health assessment, and provide a reference for the sustainable management of regional rivers and the construction of the ecological environment.

2. Evaluation Model of River Ecological Security

2.1. RBF Neural Network Model

To enhance the evaluation quality of the evaluation model designed for this study, the following assumptions are made. First, the ecological security level of the selected research cases did not change significantly during the evaluation period. The ecological safety of the second river can be measured quantitatively by objective indicators. A radial basis neural network (RBF, radial basis function neural network) is composed of an input layer, a hidden layer, and an output layer (Appendix A). It consists of a three-layer network, as shown in Figure 1. The input layer is composed of signal source nodes. The second layer is the hidden layer. The transformation function of the second layer adopts RBF. The third layer is the output layer, which responds to the input mode.

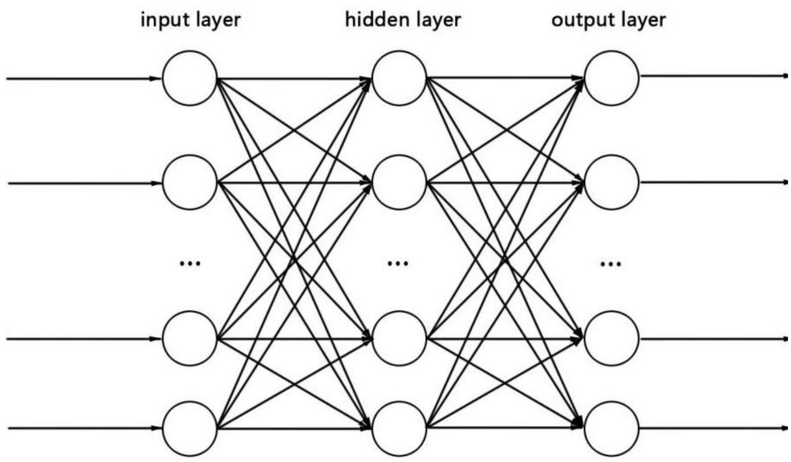

Figure 1. Structure diagram of RBF neural network model.

Inseparable problems are linearly separable in high-dimensional spaces. The RBF network has a simple structure, concise training, fast learning convergence speed, and can approximate any nonlinear function. Recent studies show that the RBF network is superior to the BP network in terms of approximation ability, classification ability (pattern recognition), and learning speed. The output of the RBF network is:

$$y = f_i(x) = \sum_{K=1}^{N} \omega_{ik}\varphi_k(\|x - C_k\|)^2 \tag{1}$$

Taking Gaussian function as the radial basis function.

$$\phi_K(x) = \exp(-\frac{\|x - C_k\|^2}{2\sigma_K{}^2}) \tag{2}$$

In Formula (2), x is the input sample; y is the output; C_K is the center of the Gaussian function; $\|x - C_K\|$ is the Euclidean norm; σ is the variance of the Gaussian function; ω_{ik} is the connection weight from the hidden layer to the output layer; and N is the number of nodes in the hidden layer. The steps of radial basis function network algorithm are as follows:

(1) Select a set of initial center values C_k from the input vector;
(2) Calculate the variance value:

$$\sigma = \frac{d_{\max}}{K} \tag{3}$$

In Formula (3): d is the largest distance; K is the number of C_k;

(3) Calculate $x(n)$ from input $\hat{y}_i(n)$

$$\widehat{y}_i(n) = \sum_{k=1}^{M} \omega_k \varphi[x(n), C_K, \sigma_K] \tag{4}$$

(4) Update network parameters

$$\omega(n+1) = \omega(n) + \mu w e(n)\varphi(n) \tag{5}$$

$$C_K(n+1) = C_K(n) + \mu c \frac{e(n)\omega_K(n)}{\sigma_K^2(n)} \varphi[x(n), C_K(n), \sigma_K][x(n) - C_K(n)] \tag{6}$$

$$\sigma_K(n+1) = \sigma_K(n) + \mu_\sigma \frac{e(n)\omega_K(n)}{\sigma_K^2(n)} \varphi[x(n), C_K(n), \sigma_K]\|[x(n) - C_K(n)]\|^2 \tag{7}$$

In Formulas (5) and (6):

$$\varphi(n) = \{\varphi[x(n), c_1(n), \sigma_1], \varphi[x(n), c_2(n), \sigma_2], \cdots, \varphi[x(n), c_N(n), \sigma_N]\}^T \tag{8}$$

$$e(n) = \widehat{y}_i(n) - y_d(n) \tag{9}$$

In Formulas (8) and (9), $y_d(n)$ is the expected output of the network; μ_N,μ_C, μ_σ, are the learning steps of three parameters;

(5) If the network converges, the calculation stops, otherwise, move to step 4.

2.2. GRNN Model

The generalized regression neural network (GRNN) model is a highly parallel radial basis network, which is a four-layer network. It consists of an input layer, a pattern layer, a summation layer, and an output layer, corresponding to the network input [9–14].

$X = [x_1, x_2, \cdots, x_n]^T$, and its output is $Y = [y_1, y_2, \cdots, y_n]^T$, as shown in Figure 2.

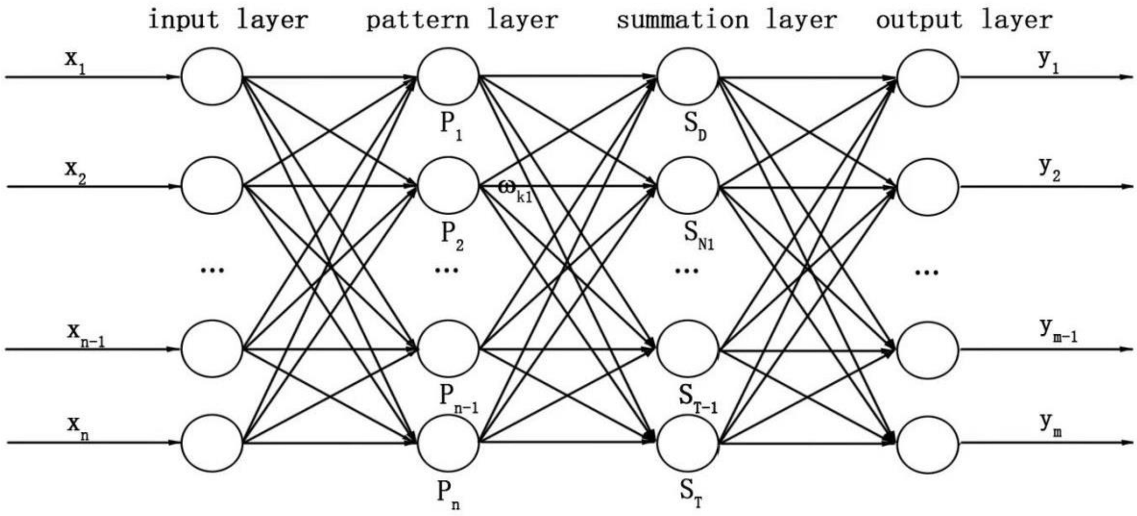

Figure 2. Structure diagram of GRNN model.

In addition, GRNN can handle unstable data. The principle of the GRNN algorithm steps are as follows:

(1) Input layer. The number of input neurons is equal to the dimension of the input vector in the learning sample, and each neuron is a simple distribution unit that directly transmits the input variables to the pattern layer;

(2) Mode layer. The number of neurons in the pattern layer is equal to the number of learning samples n, each neuron corresponds to different samples, and the transfer function of the neurons in the pattern layer is:

$$p_i = \exp[-(X - X_i)^T (X - X_i)/2\sigma^2] i = 1, 2, \cdots, n \tag{10}$$

In Formula (10), X is the network input variable; X_i is the learning sample corresponding to the i neuron; and σ is the smoothing factor;

(3) Summation layer. In the summation layer, two types of neurons are used for summation. One kind of calculation formula is:

$$\Sigma \exp\left[-(X - X_i)^T (X - X_i)/2\sigma^2\right] \tag{11}$$

Arithmetic summation is performed on the outputs of all neurons in the mode layer, the connection weight between the mode layer and each neuron is 1, and the transfer function is:

$$S_D = \sum P_i \tag{12}$$

Another type of calculation formula is:

$$\Sigma Y_i \exp\left[-(X - X_i)^T (X - X_i)/2\sigma^2\right] \tag{13}$$

The outputs of all neurons in the pattern layer are added and only summed. The connection weight between the i neuron in the pattern layer and the j molecular summation neuron in the summation layer is in the i-th output sample Y_i. The j element of the transfer function is:

$$S_{Nj} = \Sigma y_{ij} P_i j = 1, 2, \cdots, m \tag{14}$$

Output layer. The number of neurons in the output layer is equal to the dimension n of the output vector in the learning sample. Each neuron divides the output of the summation layer. The output of neuron j corresponds to the j element of the estimated result $Y(X)$, and is represented as follows:

$$y_j = S_{Nj}/S_D j = 1, 2, \cdots, m \tag{15}$$

3. Construction of the Index System for River Ecological Security Evaluation

3.1. Evaluation Indicators and Standards

This paper refers to the diversity and complexity of domestic and international river ecological security evaluation index systems and grade standards [1–6], and the contents described in references [8,15]. The experiment combines the characteristics of small and medium rivers in high-water areas and the difficulty of obtaining evaluation index data, and establishes an index system and grading standard suitable for the ecological security evaluation of rivers in high-water-level areas using the analytic hierarchy process. The flow ecological security evaluation consists of three levels: target layer A, criterion layer B, and index layer C. The target layer A is mainly used to comprehensively evaluate the ecological security status of the river. The criterion layer B is used to reflect the internal coordination of the ecological security status of the river [16]. All aspects are organically combined. The index layer C reflects the specific indicators of each criterion layer in the river ecological security evaluation, which is composed of 15 evaluation indicators reflecting river dynamics and other criteria. It is the basis of river ecological security evaluation. The following establishes the standards and scales applicable to the evaluation of the ecological security status of small- and medium-sized rivers in high-water areas, as well as divides the ecological security of rivers into five grades, as shown in Tables 1 and 2.

Table 1. Set of indicators for ecological security evaluation of small- and medium-sized rivers in Suzhou.

Target Layer A	Criterion Layer B	Index Layer C	Calculation Formula	Feature
Economic and social service function	River dynamics	Runoff per unit area/(Ten thousand m^3 Km^{-2})	The ratio of the average annual runoff of the basin to the basin area	Reflects the runoff per unit area, making rivers of different basin scales comparable
		Reach bend	The ratio of the actual length of the reach to the straight-line distance	Reflects the degree of power consumption of the river
		The proportion of soil erosion area/%	The ratio of the area of soil erosion to the total area of the watershed	It reflects the degree of surface erosion and soil and water loss in the river basin
		Average slope of the river/%	The ratio of the total drop from the source to the estuary to the total length of the river	Reflects the size of the river's dynamic and potential energy
	Ecological function	Habitat diversity index	The ratio of the quantitative indicators of current habitat diversity to the quantitative indicators of specific reference habitat diversity	Reflects the extent of damage to the current river habitat diversity
		River water quality index	The ratio of the number of water function zones that meet the water quality standards for water function zones in the whole basin to the total number of water function zones in the whole basin	Reflects the status of river water function compliance

Table 1. *Cont.*

Target Layer A	Criterion Layer B	Index Layer C	Calculation Formula	Feature
Economic and social service function	Ecological function	Guaranteed rate of ecological water demand in the river	The ratio of ecological water consumption in the river to the ecological water demand in the river	Reflects the status of ecological water use in the river
		Forest cover rate	The ratio of the forest area in the watershed to the total area of the watershed	Reflects the ability of rivers to conserve water and prevent soil erosion
		Groundwater over-exploitation	Difference between the actual annual exploitation of groundwater in the basin and the allowable exploitation and the ratio of the allowable exploitation	Reflects the degree of groundwater development and utilization in the basin
		Longitudinal continuity of the river	The product of the length of the river section where the river flow is less than the minimum ecological flow and the time period/the ratio of the total length of the river	It reflects the non-runoff attenuation along the river under human disturbance, which affects the ecological water use in the river.
	Economic and social service function	River safety flood discharge index (once in a return period of 50 years)	Ratio of safe flood discharge flow to maximum flood peak flow for a specific return period	Reflects the river's flood control function
		Adjustment ability index	The ratio of the total storage capacity of the river to the average annual runoff of the surface	Reflects the river's flood control function
		Water availability	Theoretical availability of annual average water resources and multi-year average water resources ratio of total source	It reflects the annual distribution of runoff, the difficulty of development and utilization, and the potential of water engineering to adjust and store water resources
		Out-of-channel water withdrawal rate	The ratio of annual average theoretical availability of water resources to the annual average total water resources	It reflects the degree of human society's development and utilization of water resources in the river basin and the degree of influence on the river ecosystem.
		Landscape diversity indicators	The ratio of the total amount of water withdrawn from outside, and the ratio of the amount of landscape diversity during the evaluation period to the amount of specific control landscape diversity	Reflects the impact of human construction on the diversity of river landscape after various water projects

Table 2. The grading standard of regional middle and small river health evaluation indicators.

Evaluation Indicators	Standard Grade (Ecological Safety Index)						
	I	II	III	IV	V	Upper Limit	Lower Limit
Runoff per unit area/(ten thousand m^3 Km^{-2})	50	3	25	10	5	100	2.5
Reach bend	≤1.1	1.1~1.2	1.2~1.3	1.3~1.4	>1.4	3	0.5
The proportion of soil erosion area/%	5	10	20	30	40	80	2.5
Average slope of the river/%	15	10	5	3	1	30	0.5
Habitat diversity index	1.0	0.9	0.8	0.7	0.6	1.0	0.3
River water quality index	1.0	0.8	0.6	0.4	0.2	1.0	0.1
Guaranteed rate of ecological water demand in the river	0.9	0.7	0.5	0.3	0.1	1.0	0.05
Forest cover rate	0.6	0.5	0.4	0.3	0.2	0.8	0.1
Groundwater over-exploitation	≤0	0~0.1	0.1~0.2	0.2~0.3	>0.3	0.6	0
Longitudinal continuity of the river	0	0.1	0.2	0.3	>0.3	0.6	0
River safety flood discharge index (once in a return period of 50 years)	1.0	0.9	0.8	0.7	0.6	1.0	0.3
Adjustment ability index	0.20	0.15	0.10	0.06	0.02	0.40	0.01
Water availability	≥0.40	0.35	0.30	0.25	<0.25	0.50	0.05
Out-of-channel water withdrawal rate	0.2	0.3	0.4	0.5	0.6	0.9	0.1
Landscape diversity indicators	1.0	0.9	0.8	0.7	0.6	1.0	0.3

3.2. Realization of River Health Assessment

3.2.1. Standardized Processing of Index Data

The river health evaluation indicators in Table 1 are divided into positive indicators and negative indicators. To eliminate the influence of different dimensions on the evaluation results, it is required to standardize the evaluation index data first. The indicators that have a positive effect on the river health evaluation level, such as runoff per unit area, habitat diversity index, etc., are treated as follows:

$$\hat{x} = x_i / x_{\max} \tag{16}$$

For the indicators that have a negative effect on the river health evaluation level, such as the curvature of the river reach, the proportion of soil erosion area, etc., the treatment methods are as follows:

$$\hat{x} = 1 - x_i / x_{\max} \tag{17}$$

In Formula (17), $\hat{x}$ is the standardized data; x_i is the original data; $x_{\max}$ is the maximum number in the data sequence.

After standardization, there is no magnitude difference in the numerical range of each index in the data set, which is conducive to network training.

3.2.2. Design of Training Samples

According to Table 1, the upper and lower limits (minimum and maximum values) of each evaluation factor are used as the limit value. The linear interpolation method is used to interpolate each standardized evaluation factor to obtain 50 training samples as the input of the network, and 50 samples are obtained by interpolating 0 to 1.

For example, if indicator A is 1, 3, and corresponding indicator B is 2, 4, then, according to the calculation rule of linear interpolation, when indicator A is 2, B should be (2 + 4)/2 = 3. The training sample is generated in this way. The calculation method of river health status is as follows. Input the health evaluation index data of each river into the intelligent evaluation network based on neural network. Then, the trained neural network outputs the corresponding health status classification of the river through the input data.

The training sample is applied as the output. The standardized evaluation standard value of the river ecological security index is used as the "prediction" sample to "predict". The result is used as the classification standard of the comprehensive evaluation level of river ecological security. The ecological security status of small and medium rivers in the region is evaluated and analyzed.

3.2.3. Network Training

In this paper, RBF and GRNN neural networks are applied to evaluate the health of rivers, as shown in Figures 1 and 2. Taking each evaluation index in Table 1 as the input vector, the number of neurons in the input layer is 15. The interpolation result of 0–1 is used as the output vector, that is, the number of neurons in the output layer is 1. For RBF and GRNN neural networks, there is only one threshold. There are few artificially adjusted parameters, so the network can start learning and training according to the training algorithm and training sample set. After the network is trained, the corresponding output weights of the data centers of each hidden node do not change, and the neural network at this time can perform river health assessment. In this paper, MATLAB software is applied to write GRNN and RBF neural network algorithm programs to evaluate river health status. The program adopts a cyclic training algorithm, and finally it is determined that when the SPREAD of the RBF and GRNN neural networks are selected as 1.2 and 0.2, respectively, the network achieves the best results. To verify the effectiveness of the RBF and GRNN networks, this paper selects the most widely used BP network as the comparison network. After repeated verification, the model structure is 15-62-1, and the transfer functions of the hidden layer and the output layer are tansig and logsig, respectively. The training function adopts trainingdx. The learning function of threshold and weight adopts learning. The performance function adopts mse. The expected error is set to $1 \times 10\text{-}4$. The maximum training cycle is 2000 times. After trial calculation, the network achieves better training precision and evaluation requirements.

4. Example Application

Overview of the Study Area

Suzhou belongs to the Huaihe River basin, with more than 70 major rivers belonging to the Yellow River and Huaihe River system. Larger rivers include the Huihe River, Tuohe River, Xihe River, Suihe River, Kuihe River, Xiaosuixin River, Xinbian River, and other rivers. Since the peak flow and minimum flow of these rivers are relatively low in the four seasons of the year, they are classed as small- and medium-sized rivers, and are suitable for verification of the evaluation model of small- and medium-sized rivers designed in this study. Recently, due to the development and utilization of water and soil resources in the river basin, especially agricultural production water, the proportion of water reduction reaches in the total length of the river has been increasing. The water and soil loss has intensified, which has had a negative impact on the river ecological environment. Therefore, the objective description and evaluation of the current situation of rivers is of great significance to the sustainable management of rivers and the construction of the regional ecological environment.

According to the river ecological security evaluation index system and grading standard in Tables 1 and 2, the above-trained RBF and GRNN models are applied to evaluate the standard value of the river ecological security grading evaluation and the health status of small and medium rivers in the region. The results are shown in Tables 3 and 4 below. From the analysis of Tables 3 and 4, the following conclusions can be drawn: the evaluation grades of the ecological security status of the rivers in Suzhou City are grades II to III, that is, between healthy and unhealthy. It basically reflects the current characteristics of small- and medium-sized rivers in Suzhou. It is obvious that the established RBF and GRNN river health evaluation models and evaluation methods are reasonable and feasible, and the evaluation results can be considered as the basis for comprehensive management and health evaluation of regional rivers.

Table 3. Calculation results of different networks for river ecological security classification standard value (classification basis).

Classification Standard of River Ecological Security Status	Simulation Results RBF Neural Networks	GRNN Neural Networks	BP Neural Networks
I. Safety	0.8731	0.8181	0.7563
II. General safety	0.7081	0.5943	0.5212
III. Sub-safe	0.6185	0.5168	0.3312
IV. Unsafe	0.4812	0.3757	0.2008
V. Extremely unsafe	0.3534	0.2223	0.1724

Table 4. Evaluation results of the ecological status of small rivers in Suzhou.

River Evaluation	RBF Neural Networks		GRNN Neural Networks		BP Neural Networks	
	Output Result	Evaluation Level	Output Result	Evaluation Level	Output Result	Evaluation Level
Hui river	0.6612	III. Sub-safe	0.5221	III. Sub-safe	0.3299	III. Sub-safe
Tuo river	0.6701	III. Sub-safe	0.5532	III. Sub-safe	0.5197	III. Sub-safe
Xie river	0.6912	III. Sub-safe	0.5433	III. Sub-safe	0.3611	III. Sub-safe
Sui river	0.6212	III. Sub-safe	0.5855	III. Sub-safe	0.5465	II. General safety
Kui river	0.7418	II. General safety	0.6023	II. General safety	0.6124	II. General safety
Yan river	0.7433	II. General safety	0.6154	II. General safety	0.5322	II. General safety
Tang river	0.7233	III. Sub-safe	0.5443	III. Sub-safe	0.3912	III. Sub-safe
Xinbian river	0.7282	III. Sub-safe	0.5801	III. Sub-safe	0.5101	III. Sub-safe
Hong river	0.6901	III. Sub-safe	0.5328	III. Sub-safe	0.3901	III. Sub-safe
Long river	0.7133	III. Sub-safe	0.5912	III. Sub-safe	0.4987	III. Sub-safe
Mao river	0.7313	II. General safety	0.5873	II. General safety	0.5302	II. General safety

Note: The river data of Suzhou City mainly comes from "Suzhou City Water Resources Comprehensive Planning", "Suzhou City Water Resources Development and Utilization", and so on.

This research uses the "NEU" toolbox in MATLAB software to write RBF and GRNN neural network algorithm programs. As this toolbox is particularly common, it is not be repeated in the specific content here.

(1) From Table 4, Huihe River, Tuohe River, Xiehe River, Suihe River, Tanghe River, Xinbian River, Honghe River, and Changhe River have a certain degree of river health problems. Analysis of the geographical and hydrological data of these rivers indicates that the curvature, slope, forest coverage, water and soil loss, and water pollution of the river reach are the reasons for the river being in sub-health;

(2) From the point of view of the evaluation methods, the evaluation results of the RBF and GRNN evaluation models for river health are completely consistent, and are basically the same as the evaluation results of the BP neural network;

(3) The number of neurons in the hidden layer of the BP neural network needs to be determined artificially, which is a relatively complex problem. Whether the number of neurons is reasonable or not directly affects the accuracy of prediction and measurement. Compared with BP, the RBF neural network not only has a fast learning rate, but also overcomes the disadvantage that the BP network easily falls into local extreme values. There are fewer parameters to adjust, and there is only one SPREAD (radial basis function distribution density) parameter. The size of SPREAD not only affects the approximation accuracy of the network, but also affects the prediction accuracy of the network. In the process of network design, this paper uses a loop algorithm to determine the optimal value of SPREAD to be 1.2 [14];

(4) Compared with the BP neural network, GRNN has the advantages of fast convergence speed, high prediction accuracy, and does not easily fall into local minima. GRNN needs to adjust fewer parameters, and has only one SPREAD parameter, which can make prediction faster. The network has a large computing advantage. In particular, the GRNN has a better prediction effect when the sample size is small and the noise is large, which is unmatched by the BP network;

(5) The GRNN has stronger advantages than the RBF network in approximation ability and learning speed. The network finally converges on the optimized regression surface with more samples. When there are few sample data and unstable data, the prediction effect is also excellent.

5. Discussion

The characterization and evaluation technology of river ecological security can effectively evaluate the ecological restoration effect on damaged rivers, which is of great significance to the sustainable management of rivers and the construction of the regional ecological environment. There are many methods for river ecological security evaluation, but from the perspective of evaluation principles, it can be divided into prediction model methods and multiple index methods. As the multi-index method is a comprehensive evaluation of all aspects of river characteristics and the results are more comprehensive and objective, it is a development in river ecological security evaluation. It is difficult and inappropriate to establish a conventional mathematical model of the multi-attribute evaluation system. This model can only be established by artificial intelligence, fuzzy recognition, and knowledge engineering, as they can deal with the comprehensive evaluation of the multi-attribute system. Currently, artificial intelligence methods have become some of the most effective methods in establishing and evaluating such complex systems, wherein an artificial neural network is one of the most widely used algorithms amongst such intelligent algorithms.

Therefore, this study uses the analytic hierarchy process to design the river health level evaluation index system. Then, an intelligent evaluation model of river health is constructed by applying a radial basis function neural network (RBF) and a generalized regression neural network (GRNN), both with a similar network structure, which take the evaluation index system as the input data. This is quite an academic innovation in the industry. Due to their good approximation performance and generalization ability, they can be used for river ecological health assessment, which provides a reference for the sustainable management of regional rivers and the construction of the ecological environment. The research results show that the river health intelligent evaluation model based on the AHP, RBF, and GRNN neural networks designed in this study has certain application value.

Using small- and medium-sized rivers in Suzhou as an example to carry out the verification experiment, the results demonstrate that the evaluation results of the RBF and GRNN neural networks are similar. The prediction results of RBF and GRNN are significantly different from those of the BP neural network. In the prediction results of the RBF, GRNN, and BP neural networks, the values of "extremely unsafe" are 0.3534, 0.2223, and 0.1724, respectively. The prediction levels of the RBF and GRNN neural networks for the health level of small- and medium-sized rivers in Suzhou are also more similar.

6. Conclusions

In this paper, river health assessment models based on a RBF neural network and a GRNN neural network are constructed to evaluate the health status of small- and medium-sized rivers in Suzhou. The evaluation results indicate that the prediction results of the RBF and GRNN neural networks on the health level of small- and medium-sized rivers in Suzhou are very similar, and people are more satisfied with the evaluation results of these two models. It shows that the network model established in this study can be applied to the task of river health assessment, which has certain application potential for assisting the health level assessment of small- and medium-sized rivers in China. It is able to help relevant departments take comprehensive river management measures.

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Appendix A

RBF is a type of forward network constructed based on function approximation theory, which is composed of an input layer, a hidden layer, and an output layer. The basic idea of the RBF network is to use RBF as the "base" of the hidden unit to form the hidden space, and the hidden layer converts the input quantity, and transforms the low-dimensional model input data into the high-dimensional space, so as to realize the linearity in the low-dimensional space. Flexible network structure, high fault tolerance, and robustness are suitable for solving nonlinear problems. GRNN has stronger advantages than RBF network in approximation ability and learning speed. The network finally converges to the optimized regression surface with more sample accumulation. Aside from that, the prediction effect is also better when the sample data are small.

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