International Journal of Pattern Recognition
and Artificial Intelligence
Vol. 33, No. 12 (2019) 1959039 (18 pages)

DOI: 10.1142/S0218001419590390

Application Research of Artificial Neural Network in Environmental Quality Monitoring

Kunrong Zhao[*,§], Tingting He[†,¶], Shuang Wu[‡,‖], Songling Wang[*,**],
Bilan Dai[*,††], Qifan Yang[†,‡‡] and Yutao Lei[*,§§]

[*]*South China Institute of Environmental Sciences*
MEP, Guangdong, P. R. China

[†]*Guangzhou Hexin Environmental Protection Technology Co., Ltd.*
Guangdong, P. R. China

[‡]*Guangzhou Huake Environmental Protection Engineering Co., Ltd.*
Guangdong, P. R. China
[§]*zhaokunrong@scies.org*
[¶]*ivyhtt@mail.scut.edu.cn*
[‖]*wushuang@scies.org*
[**]*wangsongling@scies.org*
[††]*daibilan@scies.org*
[‡‡]*xuwj7@mail3.sysu.edu.cn*
[§§]*leiyutao@scies.org*

Received 29 November 2018
Accepted 7 January 2019
Published 2 April 2019

With the steady growth of the economy and the rapid development of modern industrial technology, the problem of environmental pollution has increased. To continue to develop, it is necessary to thoroughly implement the sustainable development strategy, and we must pay more attention to environmental issues. One of the important management tools implemented in China for environmental management is environmental quality monitoring and evaluation. Environmental quality monitoring can scientifically evaluate the environmental quality of a region, scientifically evaluate and forecast the environmental management and environmental engineering, and provide scientific basis for environmental management, environmental engineering, formulation of environmental standards, environmental planning, comprehensive prevention and control of environmental pollution, and ecological environment construction. This paper will discuss the basic principles of neural network and the implementation process of MATLAB and in the MATLAB software implementation and display process. At the same time, the results of different parameters are analyzed through experiments, and the network parameters are constantly adjusted to improve the accuracy of the evaluation results. Taking the regional environment as an example, two monitoring methods are proposed, and a variety of neural network models are used to analyze each prediction method. Case study results show that the latter method has a better prediction effect.

[§§]Corresponding author.

Keywords: Artificial neural network; BP; fuzzy neural network; environmental quality; environmental monitoring.

1. Introduction

Environment is the place where human beings live. In order to meet the needs of life and production activities, human beings constantly ask for natural resources and energy from the environment, and the waste produced in the process of life and production is discharged into the environment. The environment should not only provide enough material resources, living space and energy for human beings, but also contain and digest all kinds of excreta produced by human activities. In view of this problem, environmental quality monitoring and evaluation arises at the historic moment.

The fundamental purpose of environmental quality monitoring and evaluation is to formulate economic development planning for relevant departments, formulate policies for sustainable energy development, determine the basis of large-scale projects, provide environmental protection for regional planning, formulate environmental rules for environmental departments at all levels, and provide comprehensive and scientific environmental management services. Therefore, environmental quality monitoring and evaluation is an effective measure to help us coordinate economic development and protect the environment. It is also an effective means to strengthen environmental management. It provides scientific basis for environmental management, environmental engineering, formulation of environmental standards, environmental planning, comprehensive prevention and control of environmental pollution, and ecological environment construction.

Environmental quality monitoring and evaluation is actually based on certain criteria to evaluate and distinguish the quality of the environmental quality model. Environmental quality assessment is based on the investigation and monitoring data of environmental pollution sources and the use of various assessment methods to assess the environmental quality of a region.[15,21,27] Environmental monitoring is an important measure to investigate and study the past and present situation of environmental quality, to use relevant scientific methods to monitor and speculate on the impact of social and economic activities on environment and environmental quality change, and to take precautions as the main policy.[2,24] The influencing factors in the environmental system are usually diverse, and the relationship between the factors is also complex. How to simulate the state relationship between the environmental system and the key factors in the system, and forecasting their respective evolution trends has been a topic of concern to many scholars. Because ANN has a strong ability to capture the nonlinear characteristics of complex systems,[4,13,26] many scholars have used this method for environmental monitoring.

If previous precipitation, mean water temperature and forecasting time are used as inputs, ANN is used to predict the Canadian river for short-term flow. Carmeron[5] and other studies show that the monitoring results are superior to the conventional deterministic model. The key of modeling is the reasonable selection of input variables, which is very important to monitor the performance of the model. With annual average temperature, annual temperature difference, precipitation in summer, autumn and winter, and the ratio of annual average precipitation as input, Jose and others used three-layer network to test and verify.[7] The results show that the prediction accuracy is better than the general regression model.

The short-term rainfall is predicted by the delay of the previous step of the spatial neighboring point. A study by Luk[18,19] in forecasting rainfall at a certain time shows that it is better to enter the time series with a one-step delay. Using 8 indicator variables as input, the BP network was used to monitor the concentration of ozone in Seoul, and Sang simulated the trend of ozone concentration over time.[12,14,23,25] Zhao Baohua and others applied BP network to forecast the Pacific Ocean temperature, and the prediction accuracy of model was very high.[3] Taking the ratio of depth and flow ratio as the input at each moment, the water conductivity coefficient and water storage coefficient of water content are taken as output. Liu Guodong and others used ANN to calculate the aquifer parameter experiment. The monitoring results show that the application method can be used to calculate the aquifer parameters accurately, simply and economically.[1,6,11,17,22] Artificial neural network (ANN) technology has strong nonlinear mapping ability and self-adaptation, parallelism, fault tolerance and self-learning ability,[10,16,20] especially suitable for solving the problem of nondeterministic prediction and classification of complex causality, it can solve the problem of environmental quality assessment and monitoring.[8,9,20] According to the requirements, the nonlinear relationship is exemplified. "In the layer-to-image measurement system, due to the influence of many factors, there is a complex nonlinear mapping relationship between the space coordinates of the object and the cross-sectional image coordinates.

With the development of some new sciences and the development of computing technology, a number of new methods for environmental quality monitoring have been proposed at home and abroad. These include genetic optimization, matter–element extension, neural network, set pair analysis, projection pursuit analysis, and new index evaluation. Each method has its own advantages and disadvantages. There is no unified method. This paper uses ANN and traditional fuzzy comprehensive evaluation method to compare and analyze environmental quality assessment, and proposes two environmental prediction and monitoring methods. The first is based on the influence of human activities and the concentration of atmospheric pollutants, and the method of predicting atmospheric concentration according to the monitoring period. The concentration is predicted according to the monitoring time: four factors such as the year, month, day and hour of the monitoring are input as the input, and the concentration is the concentration of the environmental factor, thereby achieving the purpose of predicting the quality of the atmospheric environment. The second method is based on the fact that the pollution factor is relatively stable over a certain time and space, and a known concentration is proposed to predict the future concentration. A variety of neural network models were used for each monitoring method. The innovation used in this paper is to propose a known concentration in combination with pollution factors to predict future concentrations.

2. Proposed Method

2.1. *Artificial neuron*

Artificial neurons mimic biological nerve cells and can be used to represent neural cells with multiple input, single output nonlinear nodes. Artificial neurons are a formal description of biological neurons that abstract the information processing of biological neurons and describe them in mathematical language. A typical artificial neuron model is shown in Fig. 1.

In general, as a neuron model, there should be three elements:

(1) There is a set of synapses or connections, and commonly used w_{ij} represents the strength of the connection between neuron i and neuron j, or a weight. Unlike human brain neurons, artificial neural weights can be between negative and positive values.
(2) An input signal accumulator that reflects the spatial–temporal integration function of biological neurons.
(3) An excitation function that limits the output of neurons. The excitation function limits the output signal compression to an allowable range, making it a finite value. Typically, the neuron output extends over a closed interval of [0, 1] or [−1, 1].

Artificial neurons are multi-input and single-output information processing units whose processing of information is nonlinear. So, we can abstract the neuron into a simple mathematical model:

$$U_i = \sum_{j=1}^{n} X_j \cdot w_{ij} - \theta_i,$$

$$y_i = f(u_i).$$

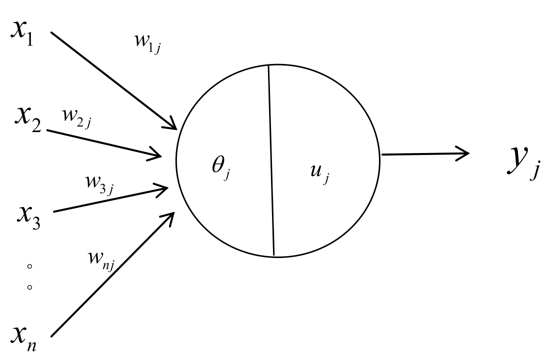


Fig. 1. Artificial neuron model.

In the formula, X_j is the input signal $(j = 1, 2, \ldots, n)$, U_i is the total input of the unit. It is considered that the unit threshold θ_i, y_i are the unit output. W_{ij} is the join weight between the units, $f(\cdot)$ is the activation function (transition function), which is generally a nonlinear form.

Sometimes for convenience, U_i is expressed as $U_i = \sum_{j=0}^{n} w_{ij} \cdot X_j$, where $w_{0j} = \theta_i, x_0 = 1$.

It can be seen that a typical artificial neuron consists of five parts.

Different levels of abstraction and simulation of biological neural network systems from different perspectives. From the perspective of functional characteristics and learning characteristics, typical neural network models mainly include perceptron, linear neural network, BP network, radial basis function network, self-organizing mapping network and feedback neural network.

2.2. *BP neural network model*

The BP neural network is a three-layer feedforward neural network, which is an input layer, an output layer, and an implicit layer. The BP network can learn and store a large number of input–output mode mapping relationships without first revealing mathematical equations describing such mapping relationships. Its learning rule is to use the steepest descent method to continuously adjust the weights and thresholds of the network through backpropagation (BP) to minimize the sum of squared errors of the network. Due to the characteristics of the feedforward neural network, the neurons of two adjacent layers are related to each other, but the same layer is not connected. Neurons are the most basic structural unit of BP neural network. The single neuron has a simple structure and a single function. However, the neural network composed of many neurons interlaced is a network system with complex and varied structures and various functions to solve many complex problems.

Forward data information calculation propagation and reverse data information BP are characteristics of BP network algorithms. When the data information is forwardly propagated, it affects layer by layer. From the input layer through the hidden layer to the output layer, the processing of the data in each layer only affects the next layer. When the output result of the output layer does not match the budget result, the network will enter the BP. BP is the correction of error, which is the adaptation of BP network. The error information is transmitted from the output layer to the input layer through the hidden layer. Each associated neuron obtains error information and recalculates the weight modification based on the error information. The BP algorithm is through such a reciprocating cycle — the forward calculation of information and the inverse control of the error, to achieve the desired input result. Through training, the sum of squares of errors is minimized, and the most accurate information is obtained by controlling the threshold and adjusting the weight.

(1) BP neural network information is forward. If X, Y, and Z are input values, hidden layer calculation results, and output layer calculation results, then the

formula from the input layer to the hidden layer is

$$Y_b = f_1\left(\sum_{a=0}^{l} V_{ab} \times X_a\right), \quad b = 1, 2, \ldots, m,$$

where f_1 is the functional relationship, V is the weight coefficient, l and m are the number of nodes of the input layer and the hidden layer, respectively. Hidden layer calculation result Y_b is brought into the output layer to calculate and the corresponding formula is

$$Z_c = f_2\left(\sum_{b=0}^{m} W_{bc} \times Y_b\right), \quad c = 1, 2, \ldots, n,$$

where f_2 is the function relationship, W is the weight coefficient, and n and m are the number of nodes, respectively. Through these two formulas, the correspondence between the input data and the calculation result can be preliminarily obtained, which is the forward propagation part of the BP neural network calculation.

Since the forward propagation calculation often has errors, the main content of the algorithm feedback mechanism is the correction of the error and the adjustment of the weight. If there are a total of P training samples, which are $X^1, X^2, \ldots X^p$, and set their desired output value to T_c^p, then the error with the actual output value Z_c^p is set to X_p (the error value of the P sample).

$$E_p = \frac{1}{2}\sum_{c=1}^{n} (T_c^P - Z_c^P)^2.$$

If E_p is less than the preset error value, the data training ends. If the value of E_p is greater than the preset error, the training continues and the weights of the neurons are further adjusted.

(2) Backpropagation of the BP network. The main function of the backpropagation of the BP network is that the control of the error is the backpropagation of the error. In addition to the error function mentioned above, several functions are associated with the error function. The output layer and hidden layer deviation formula is

$$\delta_{Rc} = f(Z_c^P) \times (T_c^P - Z_c^P),$$

$$\delta_{Rc} = f(Z_c^P) \times \sum_{a=1}^{1} \delta_{pb} \times V_{ab}.$$

In summary, the weighting factor adjustment formula for each neuron in the output layer and the hidden layer is

$$\Delta W_{bc} = \sum_{P=1}^{P} \times \sum_{c=1}^{n} \times \eta(T_c^P - Z_c^P) \times f_2(S_c) \times Y_b,$$

$$\Delta V_{bc} = \sum_{P=1}^{P} \times \sum_{c=1}^{n} \times \eta (T_c^P - Z_c^P) \times f_2(S_c) \times W_{bc} \times f_1(S_b) \times X_a.$$

The BP neural network algorithm regards the processing of data as a nonlinear mathematical optimization problem, which can reduce the error through continuous training. According to different data and requirements, the BP algorithm can set the number of nodes in each layer of the middle layer and the learning rate, which makes the BP algorithm more flexible. The BP algorithm can realize the adjustment of the weight of each neuron through continuous training, and has strong adaptability to different data and requirements, so that the BP algorithm has better fault tolerance and has a wider application range. Even so, the BP algorithm still has some shortcomings.

(1) Training takes too long. Faced with some complicated problems, the learning rate of BP algorithm converges slowly, a large amount of data requires a long training time, and the amount of data information affects the training time, which brings inconvenience to data analysis.
(2) Local minimum problem. The local minimum problem refers to the case where the BP algorithm cannot ensure convergence to the global minimum. The general control method is to use more neurons and more nodes, but this makes the data training complicated, and a few cases take longer. The BP algorithm is a nonlinear mathematical optimization problem, and nonlinearity leads to the inevitable occurrence of local minima. The BP algorithm uses the gradient of the local direction along a certain direction to gradually converge the extremes of the network. The network is usually a surface of a multi-dimensional space, and there are many regional extreme values, which makes the local minimum difficult to avoid.
(3) There is no reliable basis for the number of nodes in each layer and the control of the neurons in the network. The control of the number of nodes and the number of layers can often only be judged on the basis of experience, which makes the model setting not necessarily reasonable. If the number of layers is too small, the result will be biased and the convergence will not be obvious. When there are too many layer nodes, the operation will affect the operation speed and the fault tolerance of the data will decrease.

2.3. *Fuzzy neural network*

Because there are many factors affecting air quality, the relationship between evaluation factors and environmental quality grades is also very vague, resulting in certain uncertainty in the results of atmospheric environmental quality assessment. Therefore, this paper is adding fuzzy reasoning theory.

The fuzzy neural network mainly refers to the “this is also the same”, that the difference of objective things presents when there are intermediary transitions. There are no clear boundaries between some opposing concepts such as short and tall, old and young, poor environment, and good environment. Environment is a complex dynamic system with multi-factors coupling. Environmental quality has the characteristics of fuzziness and accuracy, uncertainty and certainty. There are also uncertainties in environmental quality assessment, such as the unreliability and inadequacy of environmental monitoring data. Variability and randomness in prediction errors and psychological factors of evaluation subjects have quantitative characteristics, so fuzzy evaluation method is introduced.

Fuzzy neural network is good at dealing with uncertain information, but it is difficult to realize adaptive learning because of its low precision and slow reasoning speed in data processing. If we combine them organically, we can give full play to their respective advantages and make up for their shortcomings. The fuzzy data is input into the neural network, and the fuzzy rules are extracted by the learning ability of the neural network, so that the fuzzy neural network has the generalization ability. This model can not only deal with accurate information, but also deal with fuzzy information, which enriches the application of neural network and fuzzy neural network.

The structure of general fuzzy control system is divided into five parts, as shown in Fig. 3.

Define variables (including input and output variables), fuzzification, knowledge base, logical judgment and clarity.

This method uses a fuzzy mathematical model:

Set the factors of environmental quality as $U = \{u_1, u_2, u_3, \ldots, u_i, \ldots, u_n\}$ $(i = 1, 2, \ldots, n)$, U is called the factor domain, where u_i is the value of the participation evaluation.

The collection of environmental quality assessment criteria is $V = \{v_1, v_2, v_3, \ldots v_j, \ldots, v_m\}(j = 1, 2, \ldots, m)$, V is called the evaluation domain, where v_i' is the set of evaluation criteria corresponding to u_i, when U and V are given, the fuzzy relationship between each environmental factor and each evaluation criterion can be expressed by the fuzzy matrix R:

$$R = \begin{bmatrix} u_{11} & u_{12} & u_{13} & \cdots & \cdots & u_{1m} \\ u_{21} & u_{22} & u_{23} & \cdots & \cdots & u_{2m} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ u_{i1} & u_{i2} & \cdots & u_{ij} & \cdots & u_{im} \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ u_{n1} & u_{n2} & \cdots & \cdots & \cdots & u_{nm} \end{bmatrix},$$

where u_i is the membership degree of the i environmental factor value which belongs to the j class evaluation standard, and R is also called the membership degree matrix. The magnitude of the role of the first single factor u_i in all factors on the factor field U can be measured by the weight matrix A: $A = \{a_1, a_2, \ldots, a_n\}$. The fuzzy comprehensive evaluation model of environmental quality is composed of two fuzzy matrices.

$$Y = A \circ R.$$

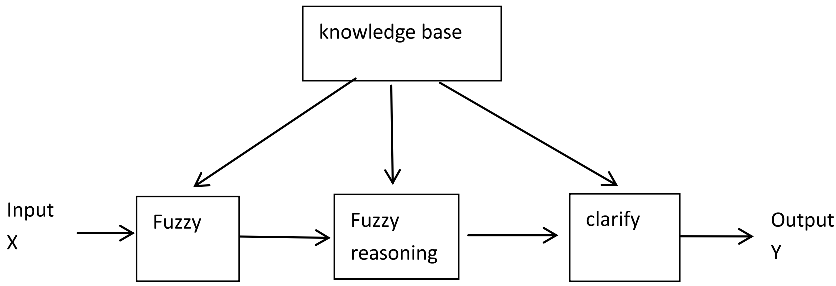


Fig. 2. Principle structure of fuzzy neural network.

The algorithm for fuzzy neural network controller parameter adjustment is as follows:

Define the error cost function as $E = \frac{1}{2}\sum_{i=1}^{m}(y_{ij} - y_i)^2$, where y_{di} and y_i represent the desired output and the actual output, respectively. $E_p = \frac{1}{2}(y_{di} - y_i)^2$.

$$\omega_m(k+1) = \omega_m(k) - \eta\frac{\partial E_p}{\partial \omega_m},$$

$$a_{ij}(k+1) = a_{ij}(k) - \eta\frac{\partial E_p}{\partial a_{ij}},$$

$$b_{ij}(k+1) = a_{ij}(k) - \eta\frac{\partial E_p}{\partial a_{ij}}.$$

2.4. *Feature selection*

Generally speaking, there are hundreds of features in the data set, so it is necessary to select the features which have a greater impact on the results for further modeling. The related methods are principal component analysis, lasso and so on. Here, we introduce data reduction to filter.

The attribute reduction algorithm based on positive region is a heuristic algorithm proposed by Pawlak, also known as Pawlak attribute importance, attribute reduction algorithm. The basic idea of the method is to first define a function of attribute importance, and calculate the importance of each attribute. The attributes are selected from large to small according to the importance value of the attribute, and then merged into the reduction set. This method of solving has great theoretical guiding significance. The algorithm requires that all elements of the power set of the conditional attribute set be examined. The advantage is that it finds the optimal attribute reduction or suboptimal attribute reduction.

The basic idea of using attribute importance as a minimum reduction is to first obtain the attribute kernel as the basis for the attribute reduction set. The importance of the attributes is calculated according to different definitions, and then the attributes are added one by one according to the importance of the attributes until the original attribute set has the same degree of dependency, then the attribute set is a reduction.

Suppose the decision table is coordinated. If there is $m_{ij} = \{a_i\}$, $\mathrm{card}(m_{ij}) = 1$, that is, there is only one condition attribute element, indicating that the other condition attributes except the attribute cannot distinguish the two records with different decisions. That is, the m_{ij} attribute must be preserved, which is consistent with the concept of the core in the decision table. Therefore, all attributes in the matrix with a combination of conditional attribute numbers of 1 are core attributes. According to the above, the disjunction of the single condition attribute feature element in the discrimination matrix is obtained as a core, and it can be seen that the less attribute contained in an item of the discrimination matrix, the greater the influence of the item on the classification. If a condition attribute appears more frequently in the discrimination matrix, the stronger the distinguishing ability of the condition attribute, the more important the condition attribute.

A function that defines the importance of the following scale attributes based on the above analysis:

$$\gamma(a) = \gamma(a) + \frac{1}{\mathrm{card}(m_{ij})}.$$

According to the definition of the discrimination matrix, m_{ij} represents the set of attributes on the basis of which the object can be distinguished, the reduction is a minimum subset of the original attribute set, and the reduction has the same classification ability as the entire attribute set. Therefore, the intersection of the reduction and all items m_{ij} of the discrimination matrix cannot be empty.

What needs further study:

(1) Efficient attribute reduction algorithm. Although scholars continue to research new algorithms and think of many ways to improve the efficiency of attribute reduction algorithms, they have not made breakthroughs. Therefore, new and more efficient attribute reduction algorithms are still worthy of study.
(2) Research on dynamic data. In real life, people often add, delete, and modify data in the database, and the data is constantly updated. Therefore, the dynamic knowledge reduction of large databases is also an area that needs to be studied at present.
(3) Attribute reduction methods suitable for large data sets. In real life, with the rapid development and wide application of database technology and the explosive growth of data in databases, people need an effective reduction method to find useful information from massive data. Processing large data sets requires a large amount of memory space, and in terms of spatial complexity, the traditional attribute reduction method is not enough to solve the problem. There is currently no attribute reduction algorithm that is very suitable for handling large data. Efforts to find an attribute reduction method suitable for large data sets is the direction of many researchers' efforts.

(4) At present, attribute reduction generally deals with discrete values. For example, it is important to study how to discretize continuous data reasonably, so that it can better acquire knowledge from information systems.

3. Experiments

The Neural Network Toolbox is one of many toolboxes developed in the MATLAB environment. It is a set of typical neural network tool functions based on neural network theory and constructed with MATLAB language. It includes many tool functions related to neural networks. MATLAB provides a powerful and convenient tool for the application research of neural networks. In the research process of this paper, this paper uses MATLAB software as the platform for network structure generation and network training and simulation.

The computer configuration is as follows:

(1) Processor: Inter i7
(2) Memory: 8GB
(3) Operating system: Windows 10, 64 bit
(4) Software application: MATLAB 2017

The local atmospheric environmental quality measured data is used as sample data of the model to assess the local urban environment. Through the comparative analysis of the application process and evaluation results of the two ideas, the advantages and disadvantages of the models are compared. The whole simulation process is designed and calculated using MATLAB software.

4. Discussion

The experimental monitoring project in this paper takes the monitoring value of sulfur dioxide (SO2) as an example, and takes the four factors of the year, month, day and hour of the monitoring as input, and outputs the concentration of SO2 to achieve the objective of atmospheric environmental quality prediction. This paper proposes two methods and combines case analysis. SO2 is recognized as the most important corrosive gas in the atmosphere and can accelerate the corrosion process of most metals. Therefore, it is necessary to monitor SO2 and establish accurate and sensitive measurement methods.

The sample data is divided into training samples and simulation samples. The training sample is the basis of network training. It provides a mapping relationship between input and output, which determines the network model problem after sample training. Only when enough sample points are evenly distributed throughout the space, the fitted function is sufficiently representative, and the sample data is also used to test the accuracy of network simulation.

1. Predict concentration according to monitoring time
In this paper, the existing data is processed, the blank value in the monitoring data is removed, and then the annual average environmental quality of each factor is

Table 1. Part sample example.

Training Input Value				
Year	Month	Day	Hour	SO_2 Monitoring Value
1	1	11	7	0.009
1	1	11	9	0.009
1	1	11	15	0.009
2	5	14	7	0.045
2	5	14	9	0.046
2	5	14	15	0.026
3	1	8	15	0.196
3	1	8	19	0.102
3	1	9	7	0.038
8	10	19	15	0.096
8	10	19	19	0.042

calculated. A total of 440 sample data are obtained, and the first 400 groups are used as training samples, and the remaining 40 groups are used as simulation samples. Some sample data are shown in Table 1.

Firstly, the network structure and parameters are determined. The BP network model is still used in this prediction. The following is the continuous debugging of the number of training and the number of hidden layers in the network parameters. The specific debugging steps are as follows:

(1) Determine the basic network structure, the network has 1 hidden layer, and the number of training is 1000 times.
(2) Increase the number of trainings, modify the statement and get the error.
(3) Increase the number of hidden layers, become two hidden layers, and modify the statement and get the error.
(4) Increase the number of nodes in the second hidden layer to 4, modify the statement and obtain the error.
(5) Increase the number of nodes in the hidden layer to 8, modify the statement and get the error.

After continuously adjusting the network parameters, the error is small, and the simulation training error is shown in Fig. 3.

It can be seen from the simulation results that the predicted results are not ideal and the gap is a bit large. Analysis of the reasons may be that the concentration of atmospheric pollutants is not only related to monitoring time, but also related to many other factors. For example, monitoring data may be more affected by meteorological and human factors.

In order to improve the prediction accuracy of the network, this paper considers the selection of training samples, such as removing some abnormal points of monitoring results, only considering the general law of the atmospheric environment changing with the monitoring time. The specific operation is to remove the sample

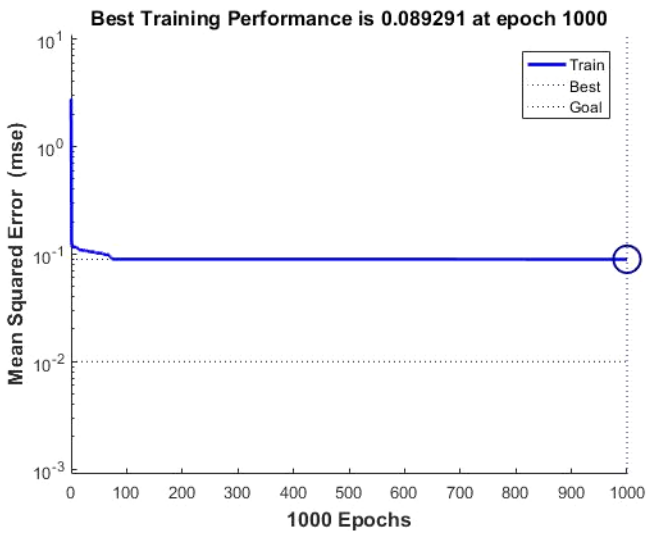


Fig. 3. Simulation error training diagram.

with the monitored value greater than 0.3 and the remaining 364 sample sizes, then select the remaining 324 samples as the training samples, and the remaining 40 groups are used as the simulation samples. The simulated samples are trained, and then the predicted values are obtained by simulation. Select 10 simulation results for comparison, as shown in Fig. 4.

From the experimental simulation results, the biggest gap is only 0.481, and the minimum gap is 0.078. After the sample data is processed, the simulation effect is better, which can reflect the overall change trend, but the overall effect is still poor, and the reasons are analyzed: (1) The selection of network model sample parameters has a great influence on the prediction results. It is necessary to continuously adjust the sample parameters to improve the accuracy of prediction; (2) The input factor of the network is only one variable of monitoring time, which is one-sided. The concentration of SO2 in the atmosphere is not only related to the monitoring time, but

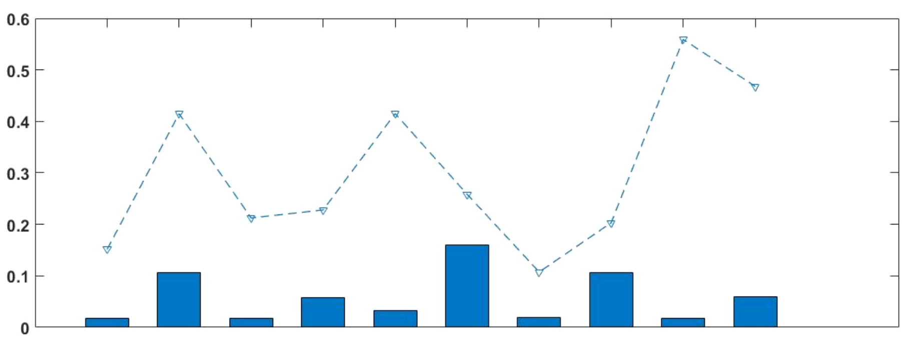


Fig. 4. Comparison of simulation results.

also related to many other factors, such as meteorological factors, human factors, etc. If the data of related factors can be collected, the accuracy of network simulation can be improved.

2. Predict future concentrations based on known concentrations
According to the monitoring value, the daily mean value of SO2 is obtained. The monitoring data of the first four days of each month are input. The fifth day's environmental monitoring value of SO2 is normalized as output. The normalized calculation method is dividing each monitoring value by the maximum monitoring value.

After processing, the total sample size was 56 groups, the first 50 samples were selected as training samples, and the remaining 6 groups as simulation samples. Some examples of training samples are shown in Table 2.

The data is verified to select different number of hidden layer nodes, and the network is trained to obtain the corresponding error, as shown in Table 3. MSE represents the output error of the training samples after network training, and res represents the error of the sample simulation results.

Use MATLAB to simulate the comparison. The comparison of the predicted results is shown in Fig. 5.

Comparing the above test values with the actual value pairs, it can be seen that most of the prediction results are close to the actual results, and there are also a few points with large prediction biases. In BP network, when the number of hidden layers is 8, the simulation effect is the best. It can be seen that less the layers there are, the better. Increasing the number of hidden layer nodes can increase the number of local minima, and too many hidden layer points may cause the network to fail to converge. The radial basis network points 4, 7 and 11 have larger errors, and the prediction errors of BP network points 4 and 11 are bigger.

From the experimental results, the prediction samples with large errors are analyzed. It is found that the monitoring values of 4, 7, and 11 are unstable and the

Table 2. Part examples of training samples.

Serial Number		1	2	3	4	5	6
Input and output	First day	0.03625	0.005	0.005	0.015	0.01325	0.04675
	The second day	0.0165	0.038	0.01	0.0685	0.018	0.033
	The third day	0.005	0.04125	0.0105	0.0195	0.005	0.03875
	The fourth day	0.015	0.043	0.04525	0.0225	0.005	0.005
	The fifth Day	0.005	0.029	0.005	0.01575	0.009	0.04325
	Normalization	0.01842	0.10681	0.01842	0.05801	0.03315	0.1593

Table 3. Network training and simulation error comparison table.

N	3	4	5	6	7	8	9	10	11	12
MS(e-5)	16.442	19.146	16.497	12.006	14.650	20.360	5.703	7.806	3.623	7.513
res	0.033	0.208	0.094	0.070	0.282	0.069	0.059	0.067	0.541	0.309

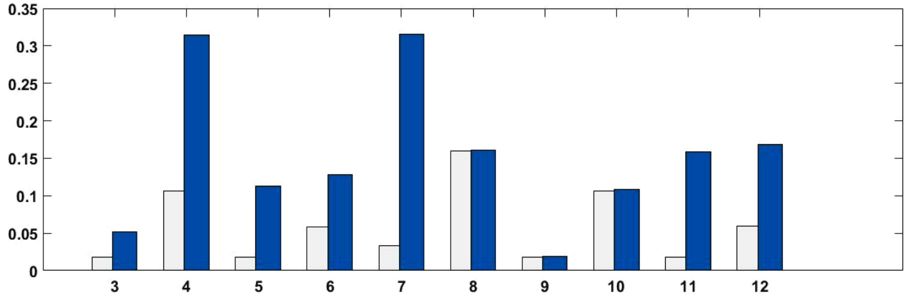


Fig. 5. Simulation result error comparison histogram.

magnitude of the change is large, which may be caused by human or meteorological factors, which causes the atmosphere to change the original changes in law.

When the second method is used to predict the future concentration according to the known concentration, the number of consecutive days of input should be appropriate. Too little cannot show the law of environmental quality change, and too much data redundancy will affect the accuracy, and other monitoring outliers will have a greater impact on the prediction effect. It can increase the preprocessing of data and obtain better simulation results through network training simulation.

5. Conclusions

This paper studies the development process, basic principles and algorithms of ANN, through the implementation and display process of MATLAB software. Two network models were selected to evaluate the atmospheric environment through network design, network training, and simulation. The results obtained by different parameter selection are analyzed and the accuracy of the evaluation results is improved by continuously adjusting the network parameters. Two environmental predictions are used and combined with the case analysis as follows: First, the concentration is predicted based on the monitoring time. The four factors of the monitored year, month, day and hour were used as inputs, and the concentration of environmental factors was predicted by experimental simulation. Through network design training, the simulation results are not good. The reason may be that the environmental monitoring value is not only related to the monitoring time. If more comprehensive factors can be collected as input, the accuracy of prediction will be improved. The second is to predict future concentrations based on known concentrations. At the end of the paper, the monitoring data is used as input to predict the environmental monitoring value, and the simulation effect is better. Using the monitoring data of the previous few days as input, predicting the environmental monitoring value for the next day, the simulation effect is better. After analysis of the simulation results of the two methods, the following points should be noted in the process of environmental prediction: (1) select appropriate network parameters; (2) have sufficient prediction samples; (3) the number of days input should be appropriate, excessive data redundancy affects accuracy; (4) data preprocessing can be increased.

References

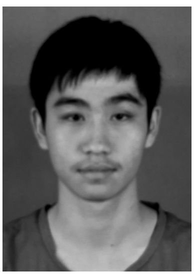
1. M. Alidina, D. Li and J. E. Drewes, A research on customer segmentation theories and their application strategies, *Water Res.* **56**(6) (2014) 172–180.
2. A. Barron and P. Hultén, Exploring corporate lobbyists' perceptions of prospective coalition partners in Brussels, *Environ. Plan. C Gov. Policy* **32**(6) (2014) 963–981.
3. Y. Cao, L. Tian and H. Zhao, The application of BP neural net real-time data forecasting model used in home, in *Conf. Cyber Technology in Automation, Control, and Intelligent Systems* (IEEE, 2015), pp. 1486–1490.
4. N. Darajeh, A. Idris, H. R. Fard Masoumi *et al.*, Phytoremediation of palm oil mill secondary effluent (POMSE) by chrysopogon zizanioides using artificial neural networks, *Int. J. Phytoremediation* **19**(5) (2016) 413–424.
5. Elrashidi, A. Moustafa, A. Cathy *et al.*, Annual precipitation and effects of runoff nutrient from agricultural watersheds on water quality, *Soil Sci.* **178**(178) (2013) 679–688.
6. Z. Feng, S. Liao, W. Niu *et al.*, Improved quantum-behaved particle swarm optimization and its application in optimal operation of hydropower stations, *Adv. Water Sci.* **26**(3) (2015) 413–422.
7. S. Ghaith, M. Wang, P. Perry *et al.*, Software contention aware queueing network model of three-tier, in *Conf. Performance Engineering* (ACM, 2014), pp. 273–276.
8. A. Giardini, M. T. Martin, C. Cahir *et al.*, Toward appropriate criteria in medication adherence assessment in older persons: Position Paper, *Aging Clin. Exp. Res.* **28**(3) (2016) 371–381.
9. H. Huang, B. Chen and C. Liu, Safety monitoring of a super-high dam using optimal kernel partial least squares, *Math. Probl. Eng.* **2015**(12) (2015) 1–13.
10. IEEE. IEEE Transactions on Computational Intelligence and AI in Games (T-CIAIG), *Comput. Intell. Magazine IEEE* **7**(2) (2017) 13–13.
11. G. Jia, Y. Bai, X. Yang *et al.*, Biogeochemical evidence of Holocene East Asian summer and winter monsoon variability from a tropical maar lake in southern China, *Quat. Sci. Rev.* **111** (2015) 51–61.
12. Y. H. Kang, S. K. Song, M. K. Hwang *et al.*, Impacts of detailed land-use types and urban heat in an Urban canopy model on local meteorology and ozone levels for air quality modeling in a coastal city, Korea, *Terr. Atmos. Ocean. Sci.* **27**(6) (2016) 877.
13. Y. H Wang, Characteristics of complex systems germane to Chaos/Complexity theory and SLA, 2014, pp. 148–149.
14. C. H. Kim, S. U. Park and C. K. Song, A simple semi-empirical photochemical model for the simulation of ozone concentration in the Seoul metropolitan area in Korea, *Atmos. Environ.* **39**(30) (2005) 5597–5607.
15. M. Kumar, Y. H. Mao, Y. H. Wang, T. R. Qiu, C. Yang and W. P. Zhang, Fuzzy theoretic approach to signals and systems: Static systems, *Inf. Sci.* **418** (2017) 668–702.
16. R. Kumari, A. Asthana and V. Kumar, A novel approach of restoration of digital images degraded by impulse noise, *Int. J. Comput. Vis. Image Process.* **4**(2) (2014) 1–17.
17. Y. Liu, G. Liu, X. U. Tao *et al.*, Sensitivity analysis of parameters on groundwater numerical model of multi-layered aquifer, *Environ. Sci. Technol.* (2014).
18. K. C. Luk, An application of hydroinformatic tools for rainfall forecasting, Thesis, 1998:752.

19. K. C. Luk, J. E. Ball and A. Sharma, An application of artificial neural networks for rainfall forecasting, *Math. Comput. Model.* **33**(6) (2001) 683–693.
20. X. Ai and A. M. Zsaki, Stability assessment of homogeneous slopes loaded with mobile tracked cranes–An artificial neural network approach, *Cogent Engineering* **4**(1) (2017) 1360236.
21. M. V. A. Martins, N. Zaaboub, L. Aleya *et al.*, Environmental quality assessment of bizerte lagoon (Tunisia) using living foraminifera assemblages and a multiproxy approach, *Plos One* **10**(9) (2015) e0137250.
22. C. Mu, T. Zhang, Q. Wu *et al.*, Stable carbon isotopes as indicators for permafrost carbon vulnerability in upper reach of Heihe River basin, northwestern China, *Quat. Int.* **321** (71–77) (2014) 71–77.
23. R. Ryoo, H. J. Sang and S. Jun *et al.* ChemInform Abstract: Iron-Facilitated Iodine-Mediated Electrophilic Annulation of N,N-Dimethyl-2-alkynylanilines with Disulfides or Diselenides, *Advanced Synthesis & Catalysis* **43**(13) (2010) 2739–2748.
24. S. Stern, Estimating local prevalence of mental health problems, *Health Serv. Outcomes Res. Methodol.* **14**(3) (2014) 109–155.
25. Q. Yang, D. M. Cunnold, Y. Choi *et al.*, A study of tropospheric ozone column enhancements over North America using satellite data and a global chemical transport model, *J. Geophy. Research Atmospheres* **115**(D8) (2010).
26. Z. Zeng, H. Yang, R. Zhao *et al.*, Nonlinear characteristics of observed solar radiation data, *Sol. Energy* **87**(1) (2013) 204–218.
27. W. P. Zhang, J. Z. Yang, Y. L. Fang, H. Y. Chen, Y. H. Mao and M. Kumar, Analytical fuzzy approach to biological data analysis, *Saudi J. Biolog. Sci.* **24**(3) (2017) 563–573.

Kunrong Zhao was born in Meizhou, Guangdong, P. R. China, in 1979. He received the Doctor's Degree from Sun Yat-sen University, P. R. China. Now, he works in South China Institute of Environmental Sciences, MEP. His research interests include environmental engineering, computational intelligence, and information security.

Tingting He was born in Guangzhou, Guangdong, P. R. China, in 1993. She received the bachelor's degree from GuangDong University of Finance & Economics, P. R. China. Now, she works in Guangzhou Hexin Environmental Protection Technology Co., Ltd. Her research interests include environmental assessment, big data analysis and information security.

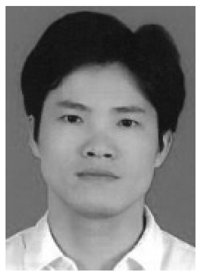
Shuang Wu was born in Beitun, Xinjiang, P. R. China, in 1990. She received the Master's degree from Northwest Normal University, P. R. China. Now, she works in South China Institute of Environmental Sciences, Ministry of Environmental Protection, Guangzhou Huake Environmental Protection Engineering CO.LTD. Her research interests include environmental planning and management.



Songling Wang was born in Ledong, Hainan, P. R. China, in 1993. He received the bachelor's degree from Qingdao University of Technology, P. R. China. Now, He works in South China Institute of Environmental Sciences, MEP. His research interests include computational intelligence, information security and big data analysis.

Bilan Dai was born in Meizhou, Guangdong, China in 1995. She received a bachelor's degree from Guangdong Ocean University. At present, she is working in South China Institute of Environmental Sciences, MEP. Her research direction is the comprehensive development and utilization of environmental information resources.

Qifan Yang was born in Maoming, Guangdong, China, in 1995. He received the bachelor's degree from GuangDong University of Finance & Economics. Now, he works in Guangzhou Hexin Environmental Protection Technology Co., Ltd. His research interests include cloud security, chaos encryption and information security.



Yutao Lei was born in Huizhou, Guangdong, P. R. China, in 1978. He received the Master's Degree from Guangdong University of Technology, P. R. China. Now, he works in South China Institute of Environmental Sciences, MEP. His research interests include environmental engineering and environmental assessment.