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Neural Network in the Forecast of Compensation for Ecological Environment Damage Caused by Trade

Ying Liu[a] and Yetong Xi[b*]

College of Chemistry and Environment, Geely University of China, Chengdu 641423, Sichuan, China
[a]s_liuying@bgu.edu.cn
[b]xiyetong@bgu.edu.cn
**Corresponding Author*

Abstract: *With the rapid growth of China's trade, the aggravation of environmental damage, research on trade growth and environmental damage forecasting issues is of great significance for the formulation and coordination of trade policies, environmental policies, and industrial policies. This article mainly studies the application of neural network in the prediction of compensation for ecological environment damage caused by trade. In this paper, the neural network model is applied to time series forecasting and panel data forecasting respectively, and the MATLAB tool is used to simulate the model, and the environmental damage compensation caused by trade is predicted. After L = 7613 iteration training, the total error value gradually decreases, and the given total error accuracy is 0.001. At this point, training is complete. After training, the BP neural network has been able to correctly predict these training samples. The prediction accuracy of this study reached 98%. This shows that the BP neural network model established in this paper not only meets the overall classification accuracy, but also has high accuracy in predicting the compensation of the ecological environment damage of each sample data. The research results show that the model is applied to the prediction of compensation for eco-environmental damage caused by trade. It has the advantages of fewer samples, high prediction accuracy, and simple calculation. It provides a new way to study the prediction of environmental damage caused by trade.*

Keywords: *Neural Network, Ecological Environment, Environmental Damage, Compensation Forecast, Trade Growth*

1. Introduction

With the acceleration of economic globalization and trade liberalization, environmental issues have increasingly attracted the attention of the world and become one of the major issues facing mankind. A series of global environmental problems have emerged in the context of economic globalization, such as the greenhouse effect, water pollution, lack of water resources, forest destruction, food pollution, ozone layer destruction, cross-border transfer of hazardous waste, acid rain, the disappearance of tropical rainforests, biodiversity Environmental problems such as sharp declines and the mass extinction of wild animal and plant species have become barriers that restrict economic and social sustainable development.

In the field of economic forecasting, artificial neural network models have better fitting ability and accuracy than traditional multiple regression forecasting methods. Artificial neural network is an intelligent bionic model based on physiology. It simulates the thinking ability of the human brain. It has large-scale parallel computing, non-linear processing, time-varying characteristics, self-organizing, adaptive, self-learning capabilities and other characteristics. Make up for some problems that still exist in the current early warning system [1-2]. The emergence of artificial neural network theories and methods provides new possibilities for early warning systems to overcome the deficiencies of traditional methods [3-4]. This article combines neural networks to establish a model of China's trade growth and environmental damage, and predicts the impact of future trade growth on the environment.

Hu Q proposed a method to transfer information obtained from a data-rich server farm to a newly built server farm. He believes that deep learning can extract high-level representations of raw data. He introduced a deep neural network that was trained on data-rich farm data to extract wind speed patterns, and then used the data from the new farm to fine-tune the mapping. In this way, the trained network transmits information from one server farm to another server farm [5]. Jiang P proposed a generalized

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regression neural network (GRNNS) with K-fold cross-validation (GRNNSK) method for predicting landslide displacement. In addition, correlation analysis is used to find the potential input variables of the prediction model. For example, Pearson cross-correlation coefficient (PCC) and mutual information (MI) are used in this paper [6]. Kamalasri introduced a method based on Recurrent Neural Networks (RNN) to evaluate the health of hard drives with SMART attributes based on gradually changing order. Compared with simple failure prediction methods, health assessment is more valuable in practice, because it enables technicians to arrange recovery plans for different hard drives according to their urgency [7]. Collins applies a new method of environmental prevention expenditure assessment to the award process of international investment arbitration. The investment arbitration court may implement an imbalance factor model to assess the rationality of the host country 's environmental regulations that have a destructive impact on foreign investment activities, such as requirements for indirect or regulatory levies [8].

This article summarizes the theory and research methods of the relationship between trade and environment, introduces the background of China 's trade and environment issues and neural network prediction technology, and uses BP neural network to establish a multi-factor prediction and time series prediction model to predict the environmental damage caused by China 's trade , And finally analyzed the prediction results.

2. Prediction Method of Compensation for Ecological Environment Damage Caused by BP Neural Network in Trade

2.1. Mutual Promotion of Trade and Environment

From the perspective of the relationship between economic growth, environmental issues, and trade, one of the main reasons for the lag in environmental protection in many countries is that because of lagging economic development and low income levels, there is no extra financial and material investment in environmental protection. There will be a situation where development is more important than environmental protection [9]. If poverty is the crux of environmental problems, economic growth can at least partially solve environmental problems, and trade is the engine of economic growth. Through free trade, countries can produce their own products based on comparative advantage theory for their own products. Consumption and exports, while importing products that are at a disadvantage or relatively disadvantaged by the country, can not only increase the country's economic income and welfare levels, but also promote the rational allocation of production factors worldwide and reduce waste of resources. In particular:

First, free trade can bring economic development and optimal allocation of resources throughout the world, and lay a solid material foundation for the coordinated development of environment and economy. A multilateral trading system with the goal of sustainable development and the best distribution of production according to comparative advantage on a global scale is beneficial to all trading partners [10]. It can improve the allocation efficiency of resources in the world, allocate resources to the production activities with the lowest cost and the highest efficiency, so that trade can make countries with different comparative advantages and resource endowments benefit from it, and overcome the constraints on growth caused by their limited capacity [11].

Second, from a country's perspective, trade liberalization has promoted the country's economic development, thereby helping the country to concentrate more financial and material resources on environmental protection. The reason why the current environment of the developed countries is getting better is largely because of this. In the past few decades, the developed countries have gained absolute advantages in the entire international trading system by virtue of their strong economic strength and advanced science and technology. Tremendous trade benefits and promoted the rapid development of the country's economy, thereby making it more capable of engaging in the development of environmental protection projects and the improvement of environmental technologies; for developing countries, despite their disadvantages in the world trade landscape, trade liberalization The wealth created still greatly promotes the economic development of the country. Its scale is far beyond the level of domestic investment and official development assistance, and this wealth can enhance the ability to deal with local environmental issues, which in turn is conducive to The improvement of the global environmental level [12].

Third, with the continuous development of international trade and increasing foreign investment, developing countries can receive more direct investment in environmental infrastructure construction

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and operation, environmental technology and development, environmental equipment production and utilization, etc. At the same time, an open trading system can allow more advanced production technologies to enter developing countries, many of which are beneficial to environmental protection and sustainable development. In addition, free trade also expands the scope of international economic cooperation and product trade, expands the trade of products obtained by using environmentally beneficial inputs, and improves the level of environmental protection in producer and consumer countries [13-14]. As people's awareness of environmental protection increases, the huge "green market" composed of green product production, green product production technology and related services will bring new opportunities to international trade.

From the perspective of the impact of the environment on trade, the natural environment provides abundant resources and energy for international trade. Humans have processed various resources to obtain various means of production and consumption. Not only can they meet their own needs, but also surplus products can be exchanged on the market. When the market expands to the world, international trade occurs. Therefore, we can say that the natural environment is the ultimate foundation of international trade. On the other hand, environmental differences in different regions will also lead to differences in countries 'comparative interests and international division of labor, which in turn will affect the content, scale, and structure of international trade, such as oil exports from the Middle East, wheat exports from the United States, gold exports from South Africa, and Africa 's needs. Imported rice, etc., all indicate that different countries' different resource endowments and environmental differences cause their trade commodity structure to be very different [15]. At the same time, the depth and breadth of trade development in different countries also affect the development of environmental resources and the level of environmental protection in various countries.

2.2. Conflict between Environmental Protection and Free Trade Rules

The growing voice of environmental protection has on the one hand prompted various multilateral international organizations to step up the formulation of various trade clauses related to environmental protection. On the other hand, it is difficult to avoid conflicts with previous trade rules. Let us take the WTO rules as an example to further illustrate. First of all, the principle of non-discrimination is the most basic principle of the WTO. This principle applies to products. It requires that each Contracting State should treat other Contracting States in an equal manner with respect to imports and exports [16-17]. However, the problem of PPMs (Processing and Production Methods) poses a huge challenge to this principle. The principle of non-discrimination believes that products obtained by different production methods can be considered to be the same product as long as they have the same end use and physical characteristics. However, some countries that advocate environmental protection believe that different production methods will have a completely different impact on the environment. Therefore, these countries have formulated environmental standards for the processing or production methods of products, and some of them have been produced through methods that will pollute the environment or destroy the ecology. Products are restricted or prohibited. This kind of provision is clearly contrary to the principle of non-discrimination.

Secondly, with regard to the principles of tariff protection and tariff reduction, the WTO not only affirmed the status and role of tariff protection, but also required parties to gradually reduce tariffs on the basis of equality and reciprocity. However, Article 2 of GATT also authorizes member countries to impose special environmental tariffs and transit adjustment taxes on imported products for environmental protection purposes, and to export products that consume a lot of domestic resources but have little or no environmental pollution to the importing country. Levying resource export taxes or environmental surcharges, which can urge producers to use environmentally friendly production technologies and processes for production, but also increase the cost burden of producers, especially when a country pays environmental taxes in order to change its domestic products. The cost disadvantages in the international market, when levying equivalent environmental taxes or transit adjustment taxes on the same imported products, are easily considered to violate the principle of tariff concessions and provide trade protection for domestic producers [18].

Another example is the conflict between environmental protection and the principle of fair trade: it is mainly manifested in the government of a country that bears the environmental costs that should be borne by enterprises; or the formulation and implementation of relatively loose environmental standards; in disguise to domestic enterprises and their products, Provide environmental subsidies and passive subsidies to improve their competitiveness in the international market; moreover, because the cost of an enterprise's product does not include environmental costs, when it is exported in large quantities at a lower sales price, it constitutes ecological dumping. The importing country determines

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that the exporting country has provided environmental subsidies or passive subsidies to its enterprises or that the exported products constitute ecological dumping; in violation of the principle of fair trade, the importing country may impose anti-subsidy and anti-dumping duties on it in order to protect its own interests [19-20].

In addition, environmental trade measures and the principle of transparency have also created some conflicts. The transparency of trade policies and measures is very important for providing market access information, reducing transaction costs, and preventing trade restrictions and distortions [21]. However, when many countries implement their environmental protection measures, there are factors such as poor communication and human obstacles. For example, environmental subsidies, ecological taxation, and waste disposal requirements in some countries are not easy to understand in time for other countries. Contrary to the transparency principle of the WTO [22-23]. In addition, the WTO also provides developing countries with various preferential treatments in trade fields such as goods, services, intellectual property, etc., but the global ecological balance and environmental protection require the joint efforts of developing and developed countries. The responsibility and obligation to protect the global environment cannot be evaded because of economic backwardness. This is also an important manifestation of the conflict between environmental protection and the WTO’s basic rules [24-25].

2.3. Improved BP Neural Network Algorithm

While widely used, BP algorithm also has some shortcomings such as slow convergence speed, lack of effective method of selecting learning rate, easy to fall into local minimum, difficult to determine hidden layer number and hidden node number, etc. It is difficult to be competent. In response to the above problems, many improved fast learning algorithms have been proposed at home and abroad [26-27]. These fast learning algorithms can be divided into two main categories: one is the improved heuristic learning algorithm by analyzing the gradient of the error performance function, such as the momentum BP algorithm, the BP algorithm with variable learning rate, etc .; Training algorithm of numerical optimization theory, such as quasi-Newton method, conjugate gradient method, LM algorithm, SCG algorithm, etc.

(1) Momentum BP algorithm

Using the momentum method can improve the learning speed and increase the reliability of the algorithm. The momentum method reduces the sensitivity of the network to the local details of the error surface, and effectively suppresses the network from being trapped in the local minimum. The algorithm of momentum method is as follows:

$$w(k+1)=w(k)+\alpha\cdot\left[(1-\eta)\cdot\Delta w(k)+\eta\cdot\Delta w(k-1)\right] \tag{1}$$

Where $w(k)$ is the weight, $\Delta w(k)=-\frac{\partial E}{\partial w(k)}$ is the negative gradient at time k, and $\Delta w(k-1)$ is the negative gradient at time k-1. α is the learning rate, α > 0; η is the momentum factor, 0≤ η <1. The momentum term added by this method is essentially equivalent to the damping term, which reduces the oscillation tendency of the learning process, thereby improving the convergence. At present, momentum items have been added to the BP algorithm, so that the BP algorithm with momentum items has become a new standard algorithm.

(2) BP algorithm with variable learning rate

In the Momentum BP algorithm, the learning rate is a constant and remains constant throughout the training process. The performance of the learning algorithm is very sensitive to the selection of the learning rate. If the learning rate is too large, the algorithm may oscillate unstable; if the learning rate is too small, the convergence speed is slow and the training time is long. Before training, it is unrealistic to choose the best learning rate. In fact, the learning rate can be changed during the training process, so that the algorithm can be corrected along the error performance surface.

There are many ways to change the learning rate, and its purpose is to make it reasonably adjusted throughout the training process. This introduces one of these methods: a gradient descent algorithm that adaptively adjusts the learning rate. The gradient descent algorithm that adaptively adjusts the learning rate tries to stabilize the algorithm during the training process, while at the same time making the learning step size as large as possible. The learning rate is adjusted according to the local error surface. When the error tends to the target in a decreasing manner, it means that the correction direction is

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correct and the step size can be increased, so the learning rate is multiplied by the increment factor k to increase the learning rate: when the error increases beyond the preset value, it means that If the correction is too much, the step size should be reduced, so the learning rate is multiplied by the reduction factor k to reduce the learning rate, and the previous correction process that increases the error is discarded, that is

$$\alpha(k+1)=\begin{cases} k_{inc}\alpha(k) & E(k+1)<E(k) \\ k_{dec}\alpha(k) & E(k+1)>E(k) \end{cases} \tag{2}$$

(3) Levenberg-Marquardt method

The gradient descent method converges slowly, because the gradient descent method drops faster near the initial point, and when approaching the optimal value, the gradient of the gradient tends to zero, which causes the error function to decline slowly; and the Newton method can be generated near the optimal value An ideal search direction. Levenberg-Marquardt is a combination of gradient descent method and Newton method, and its iteration formula is:

$$X(k+1)=X(k)-\left(J^T\cdot J+\mu I\right)^{-1}J^Te \tag{3}$$

Where is the Jacobian matrix of the first derivative of the network error to the weights and threshold, which is the damping factor, and I is the identity matrix.

2.4. Principle of Principal Component Analysis

If $X=\begin{bmatrix} X_1 \\ \vdots \\ X_n \end{bmatrix}$ is a random variable dimensioned by m, the covariance matrix of X is

$$C_X=E\left[(X-\mu)(X-\mu)^T\right] \tag{4}$$

Among them, $\mu=(\mu_1,...,\mu_m)^T=(EX_1,...,EX_m)^T$.

Since the covariance matrix C_X of X is non-negatively definite, there must be an orthogonal matrix U for C_X, so that

$$U^TC_XU=\Lambda=\begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_m \end{bmatrix} \tag{5}$$

It can be considered that the diagonal elements λ_j satisfy $\lambda_1\geq\lambda_2\geq\cdots\geq\lambda_m\geq 0$.

At this time, if U_i is used to denote the i-th column of U, that is

$$U=(U_1U_2\cdots U_m) \tag{6}$$

If A is an m ×m matrix

$$Y\overset{\Delta}{=}AX \tag{7}$$

Then each component of Y is a linear combination of each component of X, and the covariance matrix of Y is

$$C_y=AC_xA^T \tag{8}$$

Take

$$Y\overset{\Delta}{=}U^TX=(U_1U_2\cdots U_m)^TX \tag{9}$$

Then the components of Y are

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$$Y_j = U_j^T X \tag{10}$$

At this time, the covariance matrix of Y is

$$C_Y = U^T C_X U = \Lambda = \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_m \end{bmatrix} \tag{11}$$

3. Simulation Design of Environmental Damage Prediction Based on BP Neural Network Model

3.1. Implementation of BP Network Model Based on MATLAB

MATLAB software provides a ready-made Neural Network Toolbox (NNbox for short), which provides convenient conditions for solving this contradiction. For the establishment of BP network, selection of transfer function, network training, etc., based on the introduction of NNbox related functions, the methods of programming using these functions are given.

In this paper, the neural network toolbox is used to train, train and simulate the BP neural network. The actual output value of the neural network is related to the input value and each weight and threshold. In order to make the actual output value coincide with the expected output value of the network, this paper uses a certain number of learning samples and a set of corresponding expected output values to train the network. When designing the hidden layer, this paper mainly focuses on the experiment and discussion on changing the number of nodes in the hidden layer. It is improved in the experiment until a satisfactory solution is selected.

3.2. Sample Selection

The selection of training samples is very important because the selection of training samples directly affects the learning speed and effect of the neural network. The selection of samples should consider the following five points:

(1) Ergodicity, that is, the selected samples must be representative and can cover the entire sample space;

(2) Compatibility, that is, the selected samples cannot contradict themselves. When establishing input and output learning samples, the classification should be scattered but not too fine to prevent conflicts between the samples;

(3) Density, the selected samples should have a certain number to ensure the training effect;

(4) Correlation, that is, each input value in the training sample must have a certain correlation with the target value, and the input parameters in the training sample set are preferably linearly independent.

3.3 Data Preprocessing

After selecting the data, the data needs to be pre-processed before modeling. Data preprocessing is the process of enhancing the selected clean data. This enhanced processing sometimes involves generating new data items based on one or more fields, and sometimes means replacing several fields with one field with a greater amount of information. For neural networks, it is also necessary to transform the data into a form that can be accepted by neural network algorithms. Neural network data mining can only process numerical data. Therefore, if the original data set is an image, etc., it needs to be converted into numerical data first.

Because the hidden layer of the BP neural network generally uses the Sigmoid transfer function, the neuron has a saturated nonlinear characteristic (if the total input of the neuron is far away from the threshold, the actual output of the neuron is either the maximum value or the minimum value). The total input of the neuron action function is the weight of the output of other neurons connected to it. When using the BP algorithm, to prevent the neuron from entering a saturation state, the output amplitude of other neurons connected to it must be limited. Therefore, in order to improve the training speed and sensitivity and effectively avoid the saturation region of the Sigmoid function, the input samples of the network should be normalized (or called regularization) processing, which is the real

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reason why the BP algorithm must preprocess the input data .

The data normalization process is mainly to limit the original data to a certain range and perform a series of calculation processing on the data. Normalization is also to facilitate subsequent data processing and speed up the convergence of the program when it runs. After normalization, the dimensional data can be converted to non-dimensional data, and the normalized result is limited to [0,1] or [0.1,0.9] or [-1,1] .

4. Discussion

4.1. Evaluation of Neural Network Prediction Model

In the trade indicator forecasting model, this article builds on the 18 years of data and sets up the neural network to start training the network. Use the Trainbr algorithm to train the model to make predictions and get the output results in Table 1.

Table 1: Forecast results of trade indicators

Years	Total imports and exports	Trade openness	Industry as a share of GDP	Environmental protection investment
2016	20945	0.66	0.45	2937.9
2017	23877	0.66	0.46	3298.9
2018	26089	0.66	0.46	3755.5

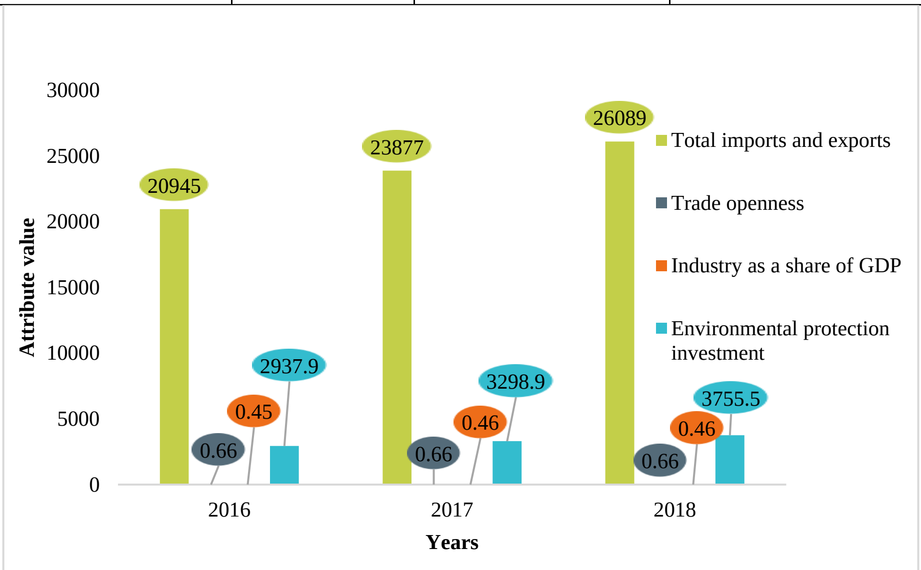

Figure 1: Comparison of forecast results of trade indicators

In the trade-environment prediction model, the original design of this paper is a BP neural network model with multiple inputs and multiple outputs. However, due to the dissatisfaction of the fitting results after training and the error of the prediction results, the model is adjusted It is a BP neural network model like single output.

On the basis of the original economic index data for 2016-2018, the five pollution indicators are studied one by one. After comparison, the model has a poor fitting degree under Trainlm algorithm and the prediction result is not ideal. Therefore, based on the predicted value of trade indicators, the model uses the model trained by the trainlm algorithm to make predictions, and the results shown in Table 2 are obtained.

Table 2: Predicted values of environmental indicators

Years	S02 (Industrial)	Industrial waste	COD (Industry)	Industrial solid waste discharge	Total solid suspended particles (TSP)
2016	2233.4	248.9	537.1	992.1	1673.7
2017	2295.8	247.8	512.7	552.5	1566.2
2018	2354.2	249.5	451.5	434.7	1437.2

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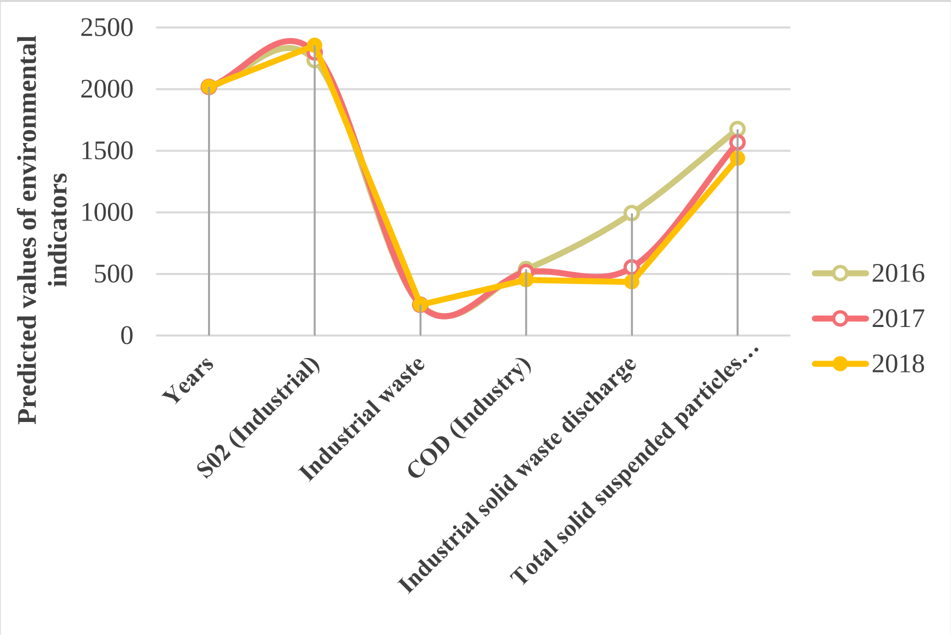

Figure 2: Predicted values of environmental indicators under the LM algorithm

As shown in Figure 1 and Figure 2, due to the fact that the actual situation of the pollution index is more discrete from year to year, there are more fluctuations, and the final prediction result is reasonable. We have reason to believe that the difference in data If it is large and there is no smooth continuity between the data, trainlm may be more suitable as a data training function for the network than trainbr. And there is a certain smooth and continuous nature between the data, it is better to use trainbr.

When using BP neural network for quantity prediction, the choice of training function will have a great impact on the results. From the experimental results of this article, trainbr learns fast when the data has a smooth and continuous nature, and does not need too many neurons; trainlm can better reflect some of the periodic properties in the data when the data dispersion is more serious. . Therefore, when making predictions, you need to analyze the continuous type of data. When performing MATLAB calculations, the main interface will also show whether the minimum value of the weighted objective function or the minimum value of the target mean square error is reached during the calculation. As long as one reaches the minimum, the calculation will stop, but sometimes it will not calculate a good result. The only solution is to experimentally add more neurons and increase the learning process.

4.2. Analysis of Ecological Environment Damage Prediction Results

From the point of view of system pressure, several indicators such as total industrial waste gas emissions, industrial solid waste generation, total industrial waste water emissions, and natural population growth rate of City account for a large weight. This is because the economic structure of City has not yet the resource-consuming development mode has changed, and traditional industrial enterprises such as electricity, chemicals, machinery, etc. still exist as the main growth points of economic development for a long time. Improvements in living conditions and medical conditions have led to an increase in the birth rate and a decrease in the mortality rate and the natural population growth rate has increased year by year. From the point of view of system status, among the indicators reflecting the running status of urban ecosystems, the weights of per capita daily water consumption and the average value of regional environmental noise are larger, while the weights of the remaining indicators are more balanced and maintained at a lower level. This shows that with the increase of the urban green area and forest coverage, urban greening is no longer the main factor affecting its urban ecological security. However, due to the concentration of chemical, paper, and power companies in City, resulting in water pollution, urban households are living with tight water and there is a risk of water source pollution. The city’s small size and large population density have caused serious noise pollution in the city, which is also in line with the actual development status. Judging from the system response, several indicators, such as the urban environmental protection investment index, the harmless treatment rate of domestic garbage, the compliance rate of automobile exhaust emissions, and the proportion of the tertiary industry as a percentage of GDP, are more heavily weighted. Measures such as increasing the pollutant treatment rate and transforming the economic development model are improving the urban ecological environment. These measures can also be reflected in the urban development plan issued by the Municipal Government in recent years.

As shown in Table 3 and Figure 3, from 2006 to 2015, the level of urban ecological security can be roughly divided into: The first stage is from 2006 to 2010, and the specific performance is that the ecological security level gradually improves and gradually changes to a critical security state. The membership of the security status is also increasing, indicating that the impact of urban ecosystem damage is gradually weakening, and people 's environmental awareness is gradually increasing; the second phase is 2011-2015, and the urban ecological security level has been greatly improved and transformed. For a safer state, and gradually transition to a safe level. The division of these three stages is consistent with the previous analysis of the urban development process of City, and is also consistent with the trend map of the main indicators of urban development.

Table 3: Eco-city prediction results

Years	Membership of each security level					Forecast result
	Safety	Safer	Critical safety	Less secure	Unsafe	
2006	0.1836	0.2243	0.3245	0.2249	0.0439	Critical safety
2007	0.1799	0.1222	0.3415	0.1716	0.1839	Critical safety
2008	0.2852	0.1835	0.3398	0.1625	0.0303	Critical safety
2009	0.2756	0.2302	0.3391	0.1322	0.0220	Critical safety
2010	0.3086	0.2201	0.3406	0.1172	0.0134	Critical safety
2011	0.3252	0.2781	0.2832	0.1017	0.0120	Safety
2012	0.2781	0.3795	0.2274	0.1037	0.0123	Safer
2013	0.3452	0.3105	0.2417	0.0912	0.0118	Safety
2014	0.3686	0.2855	0.2211	0.0707	0.0538	Safety
2015	0.3830	0.3044	0.1996	0.0587	0.0575	Safety

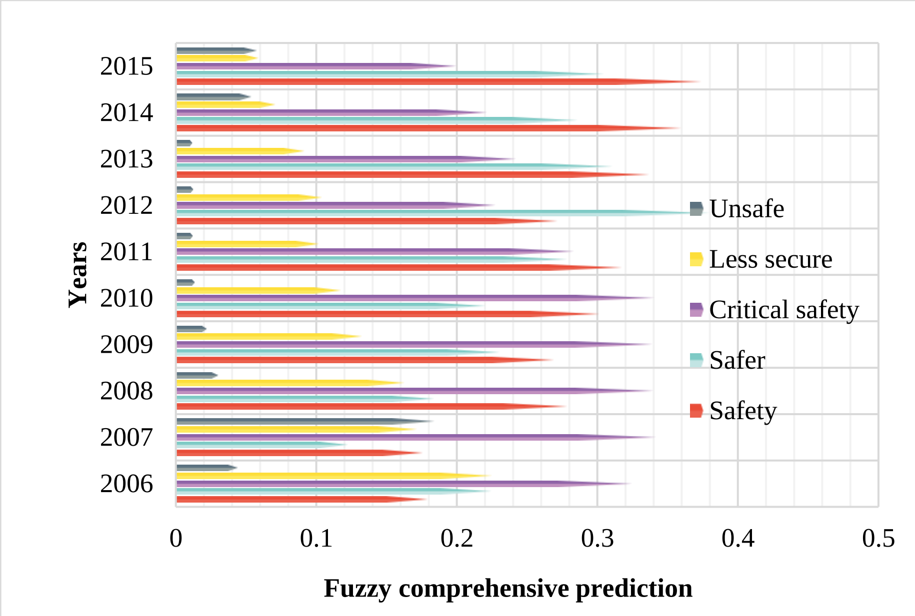

Figure 3: Eco-city prediction results

The weighted calculation results of urban ecological safety evaluation are used as input, and the urban ecological safety level of the following year is used as output. For the purpose of training the network in layers and error verification, the evaluation result data is grouped every 10 years, and finally the number of neurons in the input layer is 10 and the number of neurons in the output layer is 1.

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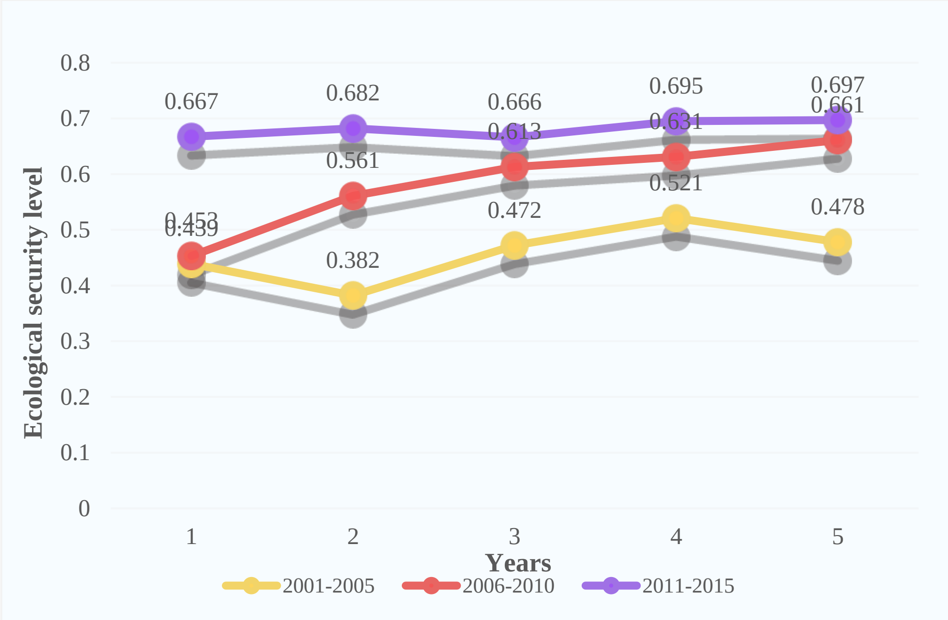

Figure 4: Weighted calculated value of ecological safety level

As shown in Figure 4, when using BP neural network for quantity prediction, the choice of training function will have a great impact on the results. From the experimental results of this article, trainbr learns fast when the data has a smooth and continuous nature, and does not need too many neurons; trainlm can better reflect some of the periodic properties in the data when the data dispersion is more serious. Therefore, when making predictions, you need to analyze the continuous type of data. When performing MATLAB calculations, the main interface will also show whether the minimum value of the weighted objective function or the minimum value of the target mean square error is reached during the calculation. As long as one reaches the minimum, the calculation will stop, but sometimes it will not calculate a good result. The only solution is to experimentally add more neurons and increase the learning process.

5. Conclusions

Neural networks are at the forefront of complex nonlinear science and artificial intelligence science, and they have the advantages of parallel computing, distributed information storage, strong fault tolerance, and adaptive learning functions. SP neural network skillfully introduces the concept of "distance weighting", so that the input data feature components can be distinguished according to their importance, so that the network convergence speed is faster, and the results of the comprehensive evaluation are closer to reality. This article explores the interrelationship between environment and trade and studies the coordination between the two.

The artificial neural network research method has large-scale parallel processing of information, has strong fault tolerance, is good at association, generalization, analogy, and reasoning, and has strong self-learning capabilities. It is good at analyzing from a large number of statistical data. Extracting macro statistical laws is suitable for quantitative research of modern logistics development strategies. This paper comprehensively and deeply researched the neural network-based trade growth and environmental damage forecasting problem, and used the neural network toolbox in MATLAB to implement a multi-layer feed-forward BP network. The results prove that the method proposed in this paper is feasible to achieve the predetermined goal. In this paper, the neural network model is successfully introduced into the quantitative prediction research on trade and environmental issues, and the prediction results within the expected error range are obtained.

Based on the comprehensive analysis of the characteristics and current research situation of the ecological environment damage caused by trade, this article discusses the ideas and specific implementation methods of the combination of the two based on neural network theory and statistical theory. The weighted method is applied to the neural network to solve the comprehensive evaluation of high-dimensional data. An improved principal component weighted SP network model is established. Several key issues in the model building are studied in depth and the model is applied to The comprehensive evaluation of ecological environment damage proves that the comprehensive evaluation method proposed in this paper is feasible and truly guarantees the accuracy and objectivity of the prediction results.

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