

Measurement and Influencing Factors Analysis of Regional Carbon Finance Development Level in China Based on ANN-RBF

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Abstract. The green development of carbon finance contributes to the rapid realization of the "double carbon strategy" goal. This paper uses the analytic hierarchy process-coefficient of variation (AHP-CVM) coupling method to measure the level of carbon finance development in China's provinces from 2018 to 2020, and uses the artificial neural network-radial basis function (ANN-RBF) method to analyze the influence of different factors on the level of carbon finance development. The results show that the development of regional carbon finance in China is affected by the new coronavirus. However, the overall trend is still rising, and there are differences in the development level of carbon finance between regions. From the perspective of influencing factors, carbon loan intensity, the proportion of added value of financial industry, the proportion of scientific research funds and the contribution rate of scientific and technological progress contribute greatly to the development of carbon finance, among which the intensity of carbon loans has the most prominent influence.

Keywords: Carbon Finance; Financial Market; Green Finance; Green Development.

1. Introduction

Carbon finance refers to financial activities aimed at reducing greenhouse gas emissions. Under the background of "low carbon transformation" of the world economy and China's "30·60" climate goal, carbon finance has become a powerful engine for China's energy transformation and low carbon economic development. At present, China has launched low-carbon pilot projects in seven cities to try CDM (Clean Development Mechanism) project transactions. However, China's carbon finance development faces problems such as imperfect market construction, insufficient policy support, insufficient product innovation, and imperfect laws and regulations.

At present, scholars have conducted much research on the measurement and influencing factors of China's regional carbon finance development level. Liu Yunzhe ^[1] constructed a carbon financial development index to measure the carbon financial development level of China's provinces, cities and regions from 2007 to 2012, and found that the overall level of carbon financial development in China was low, and the regional differences were obvious across China. Yilan et al. ^[2] constructed an evaluation system for seven carbon trading pilot cities in China with environmental binding, market resource allocation capacity and facility completion as the main indicators. They also found that the operation mechanism of the carbon trading market is not perfect, and the development level of the three evaluation indicators is fragmented. Fan Dan et al. ^[3] tested the policy effect of China's carbon trading using synthetic control and double-difference methods. It is found that carbon emission trading policy impacts carbon emission reduction and industrial structure upgrading. However, the effects are also different between different pilot provinces, and there is still room for an increase in emission reduction flexibility and economic dividends in non-pilot provinces. Wang Yong and Zhao Han ^[4] found that the launch of China's carbon trading market improved the efficiency of carbon emissions in China's provinces and widened the efficiency gap. Chen Zhiying ^[5] and others use the neoclassical theory model to establish the evaluation index system of carbon finance development level and found that China's carbon finance development level is increasing year by year. However,

its dynamic evolution is not stable, and the development level of carbon finance is unbalanced, with great differences. Zheng Qunzhe^[6] used the time series multi-index model to measure China's carbon finance development from 2014 to 2019. It was found that the overall development level of China's carbon finance was increasing year by year, but there were differences in regional development. The number of CDM projects, the number of new energy bus operations, the completion of industrial pollution control investment, and the coverage rate of urban afforestation played a promoting role in the development of carbon finance. In contrast, the urban registered unemployment rate and industrial added value would inhibit the growth of carbon finance.

Therefore, based on previous research, this paper uses the ANN-RBF model to construct an evaluation index system for China's regional carbon finance development, and uses the CVM model to determine the index weights. In this paper, taking the relevant index data (data sources) of Chinese provinces in 2018-2020 as samples, 10 index systems to measure the development level of regional carbon finance in China are constructed from four aspects, and the AHP-CVM method is used to measure this index. Then, the development stage and level of China's regional carbon finance are reasonably evaluated by using data model and index measurement. Finally, the contribution of the artificial neural network to the index is analyzed, and the important factors that influence the development of China's regional carbon finance are more accurately revealed, so as to improve China's carbon finance development system and promote the sustainable and healthy development of China's regional carbon finance.

2. Building carbon finance indicators

Based on the analysis of historical documents, this paper selects ten evaluation indexes of carbon financial market development level from four aspects of carbon financial development environment, energy efficiency, carbon financial market business and technological development^[1,6,7]. According to the connotation of carbon financial market and the influencing factors of carbon financial market development, according to the principle of logic, systematic, scientific and availability, the evaluation index system of carbon financial market development is constructed.

2.1 Carbon finance development environment

Carbon finance development environment (Y1) includes three secondary indicators, per capita GDP, the proportion of added value in the financial sector, and carbon loan intensity.

As an important index to measure economic development in economics, per capita GDP (X1) relatively objectively reflects the degree of economic and social development and the effective tool of regional carbon financial market macro-environment. The proportion of added value in the financial industry (X2) is closely related to the transformation and upgrading of China's economic development structure and promoting economic development momentum. As a branch of financial market, carbon finance can be reflected by the added value of the financial industry to a certain extent. Carbon loan intensity (X3) refers to the amount of financial institutions' local and foreign currency loans corresponding to unit carbon emissions. The larger the amount of foreign currency loans of financial institutions, the more opportunities for funds to flow to the carbon financial markets, and the greater the support for the development of carbon finance, so that we can effectively understand the financial environment of carbon financial development.

2.2 Energy efficiency

Energy efficiency (Y2) includes two secondary indicators, economic low-carbon index, and energy production elasticity coefficient.

Economic low carbon index (X4) is the ratio of total carbon dioxide emissions to total GDP, mainly used to measure the relationship between economic development and carbon emissions in a country. The smaller the economic low carbon index is, the country's economy is transforming and upgrading in the direction of high green quality, which reflects the level of financial market development to a

certain extent. Energy consumption elasticity index (X5) is the ratio of the annual average growth rate of total energy consumption to the average yearly growth rate of national economy. The lower the consumption elasticity index is, the greater the driving force of energy consumption for economic development is, and the higher the development level of carbon financial market is.

2.3 Carbon financial market business

Carbon financial market business (Y3) includes three secondary indicators: carbon market turnover, Chinese Certified Emission Reduction, and carbon market effectiveness.

The carbon market turnover (X6) can reflect the development of the carbon financial market to a certain extent. The higher the carbon market turnover is, the higher the development level of the carbon financial market is. CCER turnover (X7) has been the focus of developing carbon pilot markets in recent years. CCER trading volume can effectively grasp the effect of carbon financial markets. The carbon market efficiency (X8), that is, the ratio of the average annual price of the regional carbon quota market to the average annual price of the EUA market, reflects the degree of difference in carbon emission rights prices between the domestic market and the international market. The greater the difference is, the greater the degree of price distortion is, and the lower the market efficiency is. When processing the data, the average annual price of EUA market in the EU uses the euro price multiplied by the average exchange rate between the euro and CNY in the current year to reduce the error impact of the exchange rate on the measurement of effectiveness.

2.4 Technology Development

Table 1. Carbon Financial Indicators

Goal Layer	I Level indicators	II Level indicators	Calculating Method	Code	Ref
Carbon Finance Development Level	Carbon Finance Development Environment (Y1)	Per Capita GDP	Ratio of total GDP to total population	X1	[4]
		Proportion of Added Value in the Financial Sector	The proportion of financial industry added value to GDP added value	X2	[5]
		Carbon Emission loan Intensity	Financial institutions' foreign currency loans corresponding to unit carbon emissions	X3	[5]
	Energy Efficiency (Y2)	Economic Low-carbon Index	Ratio of total carbon dioxide emissions to total GDP	X4	[5]
		Energy Consumption Elasticity Coefficient	Ratio of annual average growth rate of total energy consumption to annual average growth rate of national economy	X5	[5]
	Carbon Financial Market Business (Y3)	CCER Turnover	Data from China Nuclear Voluntary Emission Reduction Market	X6	[3]
		Market Trading Volume	Source Carbon Market Trading Data	X7	[3]
		Effectiveness of Carbon Market	Ratio of Average Annual Price of Regional Carbon Quota Market to EUA Market	X8	[4]
	Development of Science and Technology(Y4)	Proportion of R & D Expenditure	Ratio of R & D expenditure to GDP	X9	[6]
		Contribution Rate of Science and Technology Progress	The Ratio of Technological Progress to Financial Growth	X10	[8]

Science and technology development (Y4) mainly includes two secondary indexes, R & D expenditure proportion and contribution rate of science and technology progress. R & D expenditure ratio (X9) is an important indicator to measure a country's science and technology investment scale and independent innovation capability. The increase of R & D expenditure will promote the rise of technology level. The rise in technology level will also promote the development of the carbon financial market to a certain extent. The contribution rate of scientific and technological progress (X10) is also an important indicator to measure the scale of scientific and technological investment and the independent innovation capability of a country. The higher the contribution rate of scientific and technological progress is, the stronger the role of scientific and technological progress in promoting the economy is, which reflects that the country has a stronger innovation ability and can

promote the development of carbon financial market to a certain extent. In summary, the indicators and measurement methods are listed in table 1. [3-6]

3. Construction of carbon finance evaluation index based on AHP-CVM coupling method

In order to measure the impact of the overall development of carbon finance in various regions, it is necessary to calculate the weight. A single focus on subjective or objective calculation methods will affect the evaluation results. Therefore, this paper uses the AHP-CVM coupling weight method to avoid the error caused by one-sided weighting, so that the evaluation results are more objective and reasonable.^[8]

3.1 Determination of index weight of benchmark layer based on AHP method

3.1.1 Establishment of judgment matrix c_{ij}

According to the 1-9 scale method, according to the ability of the index to reflect the nature of the evaluation object, the index is compared in pairs to obtain matrix $C = (c_{ij})_{m \times n}$, where c_{ij} represents the importance of index i relative to index j , and the value of c_{ij} is referred to Table 2.

Table 2. Scale Meaning

Indicator Judgment Comment	Scale c_{ij}
i as important as j	1
i is a little more important than j	3
i is more important than j	5
i is much important than j	7
i is extremely important than j	9
The important of i and j is between the above two	2, 4, 6, 8

3.1.2 Calculation of base layer weights

It is easy to know from the matrix theory that the weight of each factor is the eigenvector W of the matrix. This paper uses the root-mean-square method to calculate:

①Multiply the judgment matrix elements of each row to get M_i

$$M_i = \prod_{j=1}^n b_{ij} \quad (1)$$

②Calculate the n th root of M_i

$$W_i = \sqrt[n]{M_i} \quad (2)$$

③Normalize vector W_i to get W_i^*

$$W_i^* = \frac{W_i}{\sum_{i=1}^n W_i} \quad (3)$$

3.1.3 Consistency testing

Consistency test is the logical verification of the judgment matrix. Generally speaking, for the judgment matrix $C = (c_{ij})_{m \times n}$ with strict logic, it must satisfy $c_{ij} \cdot c_{jk} = c_{ik}$. Considering the complexity of specific problems and operations, errors are generally allowed. The steps are as follows:

①Calculating the maximum eigenvalue of judgment matrix

$$\lambda_{\max} = \sum_{i=1}^m \frac{(CW_i)}{mW_i} \quad (4)$$

② Calculation of consistency indicators

$$CI = \frac{\lambda_{\max} - m}{m - 1} \quad (5)$$

③ Calculation of consistency ratio

$$CR = \frac{CI}{RI} \quad (6)$$

In general, the smaller the CR value is, the better the consistency of the judgment matrix is. If the CR value is less than 0.1, the judgment matrix meets the consistency test. If the CR value is greater than 0.1, there is no consistency. The judgment matrix should be adjusted appropriately and then analyzed again.

3.2 Determination of index weight of benchmark layer based on CVM method

In order to measure the impact of the overall development of carbon finance in various regions, it is necessary to calculate the weight. For a single calculation method focusing on subjective and objective, it will affect the evaluation results. Therefore, this paper uses the AHP-CVM coupling weight method to avoid the error caused by one-sided weighting and make the evaluation results more objective and reasonable.

Firstly, the weight of the four indexes in the reference layer is calculated according to the AHP analytic hierarchy process, and the feature vector and the weight ratio of the whole are obtained by the consistency test, which is denoted as Y_{AHPi} . Secondly, the maximum and minimum normalization processing (Min-Max Scaler) is carried out on all the indexes at the index level, and the weight of each index is obtained by using the CVM variation coefficient method, denoted as β_j . Then, the final weight of each index layer in each year is obtained by the coupling formula $X_k = Y_{AHPi} \cdot \beta_j$. Finally, the geometric average of the weights for three years is taken as a unified weighted weight, denoted as X_k^* . The weighted vector aggregation of benchmark layer indicators, the weighted vector aggregation of carbon finance indicators from 2018 to 2020 and the weighted vector aggregation of full samples are respectively: Y_{AHP} , X^{2018} , X^{2019} , X^{2020} , X_k^* .

Then through $G_k^h(x) = \sum_{k=1}^n Z_{ik}^y x_k$, the carbon finance development level of 30 provinces in China from 2018 to 2020 is comprehensively scored and divided into levels and levels.

4. Construction of ANN-RBF model

4.1 ANN-RBF neural network theory

An artificial neural network (ANN) is an intelligent algorithm based on the principle of neural networks in biology. It is a branch of artificial intelligence, and a data processing model established under the inspiration of biological neural network, which is similar to the information processing technology of the human nervous system. RBF neural network is a feedforward network containing a single hidden layer. It consists of three layers: input, hidden, and output. Compared with other neural networks, its model structure has the advantages of simple structure, strong approximation ability, faster convergence rate, and easy adjustment of network structure. It has high processing efficiency and high accuracy for data.^[9]

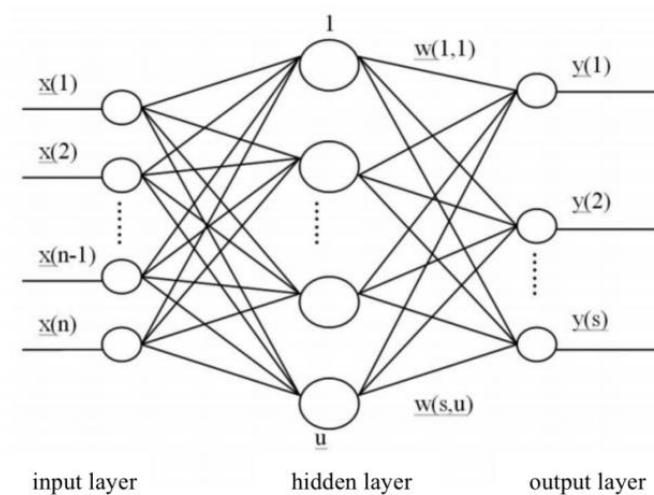


Figure 1. ANN-RBF Network Structure Diagram

4.2 Model construction

The learning process of neural network is as follows:

①Using Gaussian function excitation function, as shown in Equation (7), the nonlinear mapping of input signal in the input layer is realized:

$$R_i(x_p - c_i) = \exp\left(-\frac{1}{2\sigma^2}\|x_p - c_i\|^2\right) p \quad (7)$$

Where $x_p = (x_1^p, x_2^p, \dots, x_n^p)^T$ is the p th input sample; c_i is the center of the Gaussian function of the hidden layer; σ is the variance of the Gaussian function; and $\|x_p - c_i\|$ is the European norm.

The linear mapping from the hidden layer to the output layer is realized. The linear output function is:

$$y_i = \sum_{j=1}^h w_{ij} \exp\left(-\frac{1}{2\sigma^2}\|x_p - c_i\|^2\right), j = 1, 2, \dots, n \quad (8)$$

Among them, h is the total number of nodes in the hidden layer, w_{ij} is the linear weighted value from the hidden layer to the output layer, y_i is the actual output of the j output node in the network, and n is the number of output nodes.

If d is the expected output value of the input sample in the network, the variance σ of the hidden layer Gaussian function can be expressed as:

$$\sigma_i = \frac{1}{P} \sum_j^m \|d_j - y_j c_i\|^2 \quad (9)$$

It can be seen from the above that the RBF network algorithm mainly undergoes two stages: first, the basis function is determined according to the input samples transmitted from the input layer to the hidden layer, namely, the variance σ_i and center c_i of the Gaussian function; finally, according to the sample information, combined with the hidden layer parameters, the least square method is used to calculate the weight w_{ij} of the linear output function in the network. At the same time, in order to further improve the prediction accuracy of the network, the parameters of the output layer and the hidden layer can be corrected by combining the sample signal at the last stage.

4.3 Evaluation Index of RBF Neural Network Performance

MSE is used to measure the prediction accuracy and model performance of the established RBF neural network, where MSE is the expected value of the square of the difference between the predicted value and the real value of the model. The smaller the MSE is, the higher the prediction accuracy of the established model is. The specific calculation formula is ^[10]:

$$MSE = \frac{1}{n} \left[\sum_{i=1}^n (\hat{Y}_i - Y_i)^2 \right] \quad (10)$$

Where n is the number of samples, $\hat{Y}_i$ is the predicted value, and Y_i is the real value.

5. Empirical analysis

5.1 Object introduction and data collection

In the calculation of carbon finance index, based on the carbon finance development level index system constructed in this paper, 30 provinces in China (except Tibet and Hong Kong, Macao and Taiwan) from 2018 to 2020 are selected as the research objects. The data sources are Wind consultation, CEADs and data published in the past years of China Statistical Yearbook from 2018 to 2020.

5.2 Index calculations

Referring to many papers and expert reports, the judgment matrix c_{ij} of the first level index of the carbon financial evaluation system is:

Table 3. Judgement Matrix c_{ij}

	Y1	Y2	Y3	Y4
Y1	1	3	1	2
Y2	1/3	1	1/2	1
Y3	1	2	1	1
Y4	1/2	1	1	1.

After the analytic hierarchy process analysis, the weighted vector set of the benchmark layer index is $Y_{AHP} = \{0.36681, 0.15084, 0.28109, 0.20126\}$.

In this paper, the CI value calculated for the fourth-order judgment matrix is 0.027, and the RI value is 0.890. Therefore, the calculated CR value is $0.030 < 0.1$, which means that the judgment matrix in this study meets the consistency test, and the calculated weights are consistent.

Then, the data are brought into the entropy weight method to solve the weight of each secondary weight, and the weighted vector set of carbon finance indicators from 2018 to 2020 is:

$$X^{2018} = \{0.095, 0.108, 0.163, 0.091, 0.060, 0.115, 0.108, 0.058, 0.155, 0.046\} \quad (11)$$

$$X^{2019} = \{0.111, 0.126, 0.130, 0.102, 0.049, 0.083, 0.139, 0.055, 0.136, 0.065\} \quad (12)$$

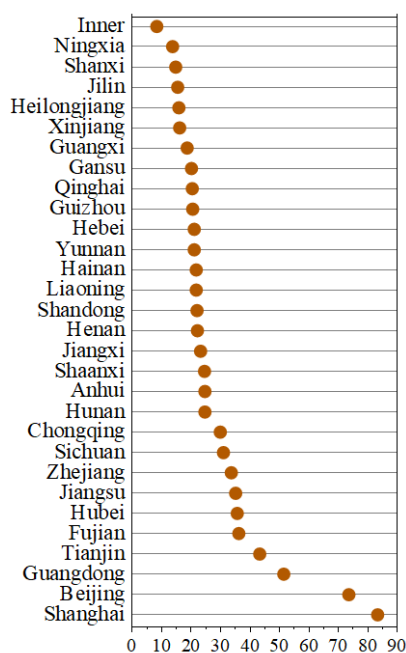
$$X^{2020} = \{0.111, 0.130, 0.126, 0.093, 0.058, 0.075, 0.147, 0.587, 0.149, 0.052\} \quad (13)$$

Then, the final weight score is determined based on the AHP-CVM coupling method. The geometric average of the weight number for three years is taken as a unified weighted weight number, denoted as f_k^* . The weighted vector aggregation results of the whole sample are:

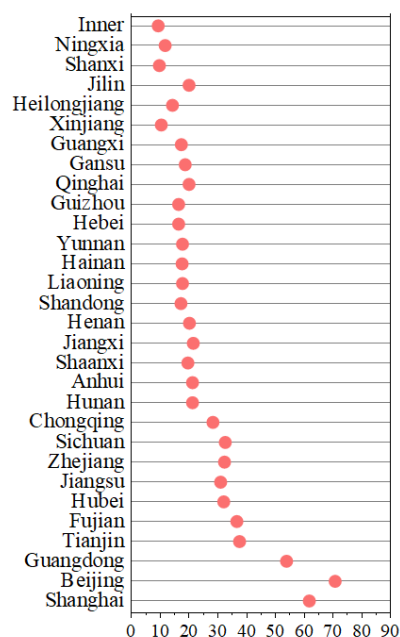
$$f_k^* = \{0.105, 0.121, 0.139, 0.095, 0.055, 0.090, 0.130, 0.057, 0.146, 0.054\} \quad (14)$$

Then, by comprehensively scoring the carbon finance development levels of 30 provinces in China from 2018 to 2020, the levels and levels are divided:

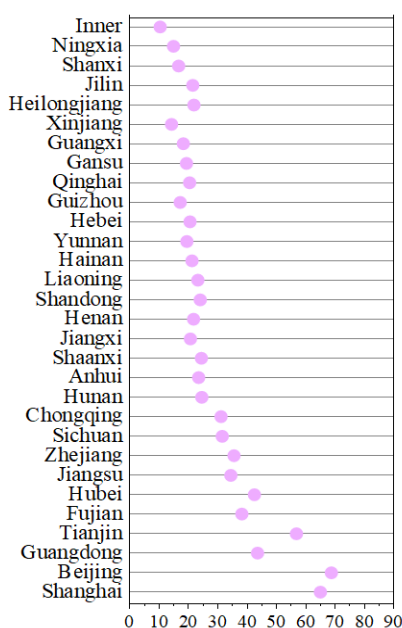
By substituting the data into $G_k^h(x) = \sum_{k=1}^n Z_{ik}^y x_k$ for calculation and sorting, Table 4 is obtained:



(a)2018 Carbon Finance Development Index



(a)2019 Carbon Finance Development Index



(a)2020 Carbon Finance Development Index

Figure 2. China Provincial Carbon Finance Development Index 2018-2020

Since 2011, China has carried out carbon emission trading pilot projects in eight provinces and cities, including Beijing, Shanghai, Tianjin, Chongqing, Hubei, Guangdong, Shenzhen and Fujian. According to Table 4, it can be seen that the carbon financial development index of the seven pilot provinces ranks in the top 10 in three years, indicating that carbon emission trading can greatly promote the development level of carbon finance in various regions. Among the pilot provinces, Beijing, Shanghai, Tianjin, Guangdong and other eastern regions continue to remain in the first rank. From the overall point of view of table 4, the development of carbon finance in the eastern region is better than that in the western region of the central region. In Table 4, the ranking of coastal provinces is concentrated in the top 60 % of all provinces, indicating that the overall development level of carbon finance in coastal areas is higher than that in inland areas.

5.3 Contribution analysis

Because the above index weight calculation process is to listen to the expert opinion on the first level index construction, and then through the entropy weight method to calculate the second-level index accounted for the first level index weight to calculate the second-level index accounted for the total index weight. However, the process does not directly reflect the influence of each secondary index on the total index. Therefore, the ANN-RBF neural network method is selected to explore the influence of secondary indicators on the total index.

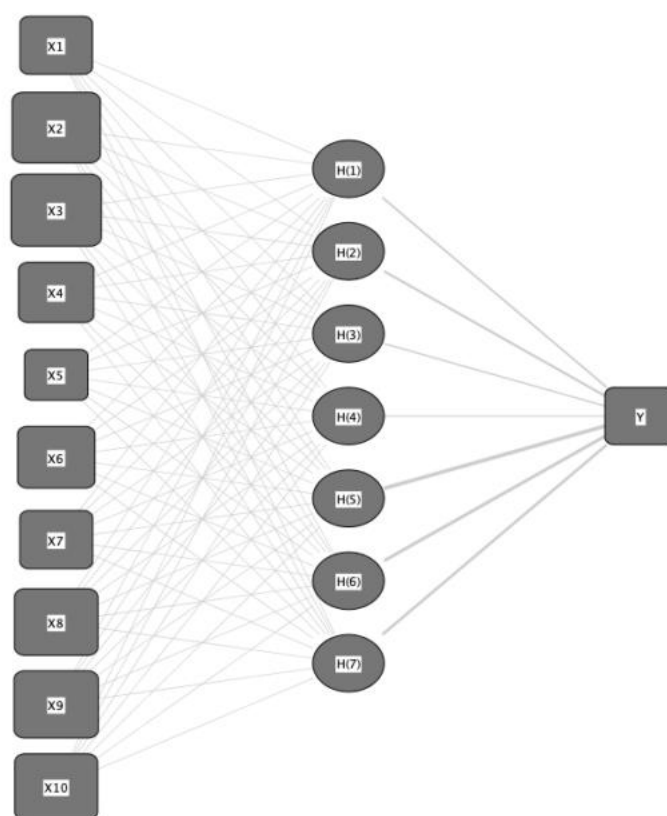


Figure 3. ANN-RBF Network Diagram

Normalized data is brought into the network for training. The training group data is 66 groups, and the test group data is 24 groups. The relative error rates for the two are 0.095 and 0.059, respectively. The accuracy of neural network results is more accurate and convincing.

Combined with the neural network constructed above, the ANN algorithm is used to measure the influence of the input layer on the output layer in the neural network, and then explore the relationship between the explanatory variables and the explained variables. [11] The specific results are shown in Figure 4.

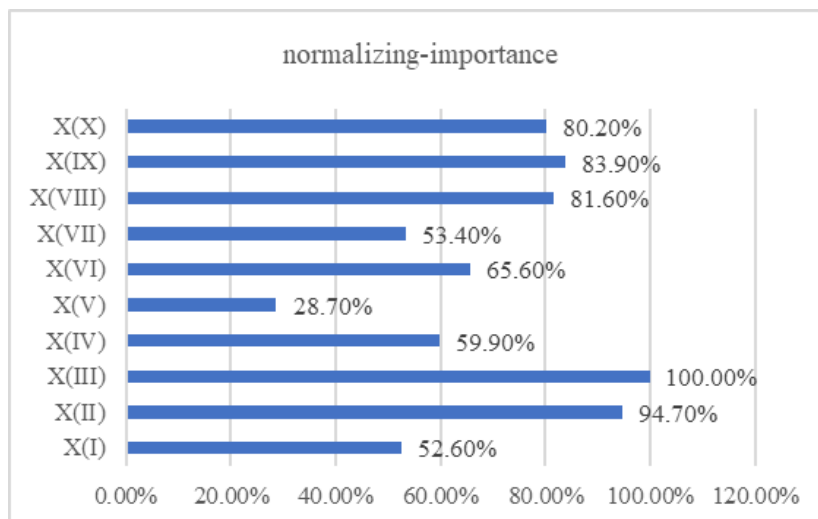


Figure 4. Importance of Normalization of Variables

From the perspective of influencing factors, carbon loan intensity, the proportion of added value of financial industry, the proportion of scientific research funds, and the contribution rate of scientific and technological progress have greatly contributed to the development of carbon finance. Among them, the impact of carbon loan intensity is the most obvious, with variable importance of 14.3%. The importance of variable is 100 %. Second, the added value in the financial industry accounts for 94.70% of the total. The least important is the indicator Energy Consumption Elasticity Coefficient, which is only 28.70%. According to the above conclusions, the following suggestions can be made:

First, continue to strengthen the intensity of carbon emissions loans, improve the green credit system, vigorously promote the advanced experience of pilot areas, and continue to play the environmental benefits of green credit.

Second, optimize the investment and financing environment of carbon emission reduction, innovate carbon emission reduction investment and financing products, vigorously develop green funds, green loans and other business, and innovate the financing mode of green emission reduction projects. Colleagues should strengthen the investment and financing business and supervision and review of carbon emission reduction to ensure its peaceful development.

Third, it is necessary to strengthen capital investment, innovate green production technology, actively cultivate low-carbon industries, and consider environmental protection and output value improvement. Green agriculture, renewable energy utilization, green service industry and high-tech industries should be developed together to form a green circular industrial chain.

Fourth, give full play to the model role of carbon trading pilot areas, lay the foundation for the promotion and construction of a complete national carbon trading market, actively promote the development of CCER projects, stable market prices, and rich market-level improve market efficiency.

6. Conclusion

Based on the academic research on carbon finance development system, this paper uses the AHP-CVM coupling model to determine the weight of each indicator and build a measurement system for the development level of China's regional carbon finance, so as to evaluate and analyze the development level of China's regional carbon finance. Meanwhile, this paper innovatively uses a high-precision ANN-RBF model to study the changes and influencing factors of carbon finance development level in 30 provinces and autonomous regions from 2018 to 2020. According to the evaluation results of regional carbon finance development, the development of regional carbon finance in China is still on the rise despite the impact of COVID-19, and the development level of carbon finance varies among regions. From the perspective of influencing factors, the carbon

emission loan intensity, the proportion of the added value of the financial industry, the proportion of scientific research funds, and the contribution rate of scientific and technological progress make significant contributions to the development of carbon finance, among which the carbon emission loan intensity has the most significant impact. Combined with the analysis of index calculation results and variable importance analysis, it can be seen that in order to promote the development of carbon finance, all localities should actively promote the comprehensive promotion of carbon trading pilot in accordance with national policies. In addition, the threshold of green credit will be lowered, and relevant policies will be given to promote enterprises to improve technology and reduce emissions to promote industrial upgrading and high-quality economic development.

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