Research on the Construction Path of China's Zero-carbon Ports from the Perspective of Marine Carbon Sink Trading

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Abstract. At present, the international market has gradually carried out research on forecasting the trading price of carbon emissions with macroeconomics and energy market as the main influencing factors, supplemented by other factors such as policy factors. In order to speed up the construction of carbon accounting system, enrich the content of China's carbon pricing mechanism and improve the carbon emission trading market, this study constructs an index system from four aspects: macro-economy, energy price, climate environment and international market, and objectively screens out the important influencing factors of carbon trading price through Lasso regression, and uses BP neural network prediction model to predict carbon trading price. [7] We should focus on reducing the proportion of coal consumption by port enterprises and increasing other clean energy consumption. This result can provide basis and reference for the construction of zero-carbon ports and the construction of ocean-port carbon trading information platform in China.

Keywords: Ocean carbon sink, Carbon trading, Zero-carbon port, Construction path.

1. Introduction

At present, in order to curb global warming, reducing carbon emissions has become the consensus of all countries in the world in the 21st century. As the transshipment node of the global supply chain, the carbon emissions of ports account for about 3% of the global carbon emissions. Therefore, in order to effectively control the growth rate of port carbon emissions, conform to the market-oriented development of marine carbon sink trading platform, and further intensify the work of energy conservation and emission reduction, relying on China's carbon pricing mechanism, its core content-carbon emission trading, guide the rational allocation of resources, encourage enterprises to transform and upgrade, and reduce the total social emission reduction cost. In this study, BP neural network model is established to predict the carbon trading price, evaluate [9].

2. Research Summary

2.1. The background of innovation of ocean-port carbon sink trading market

So far, eight regional carbon emission trading markets have been established in China. [5] Under the background of high international carbon price and China's shortage of carbon resources, we will promote the operation of China's marine carbon sink trading market and use economic means to achieve energy conservation and emission reduction and reduce carbon emissions.

China attaches great importance to low carbon, and low-carbon innovation is still a hot topic in the policy of "carbon neutrality" and the development of carbon price predicted by the carbon trading market. Since the reform and opening up, it is little known that China's economy is indeed growing substantially, but it is sad that the constraint of environment and resources is becoming more and more serious. Based on the construction of China's socialist maritime power, the acceleration of port trade and the vigorous promotion of China's "double carbon" plan in the 14 th Five-Year Plan, it is necessary to increase carbon emission reduction and increase carbon exchange. China, as the largest

carbon pool on the earth, has very little to develop, but it has great potential to increase ocean carbon sinks.

2.2. Port enterprises operating carbon trading market effect

It is an effective way to promote energy saving and emission reduction of port enterprises by using carbon pricing model to predict carbon trading market and obtaining more benefits through carbon trading market. Port enterprises can obtain funds by selling their own carbon emission rights through the carbon trading market, which can reduce the financial burden of energy conservation and emission reduction of port enterprises, promote their energy conservation and emission reduction, and then reduce the total carbon emission in China accordingly. Port enterprises can directly or indirectly reduce carbon emissions by saving energy and reducing emissions, and gain surplus carbon emission rights to participate in the carbon trading market. After trading carbon emission rights in the carbon trading market to obtain funds, port enterprises can invest in energy conservation and emission reduction, and continue to obtain surplus carbon emission rights, [6].

3. Model Construction

3.1. Data preparation

Table 1. Overview of the research level of influencing factors of carbon trading price at home and abroad

author	influencing factor	Method model	age	research contents
Liu Yueli, Hu Wei, Xing Yuantong	Economic scale factors, energy consumption intensity, energy structure	Allocation method, non-allocation method, LMDI model	2023	Study on the Influencing Factors of Carbon Emissions of Public Service Buildings in China —— Based on Two Accounting Methods of Carbon Emissions
Wei Jiang, Yifei Sun	coal consumption, industrial structure	Cross-sectional augmented error correction method, augmented mean group	2023	Which is the more important factor of carbon emission, coal consumption or industrial structure?
Zhao Zhixuan	Energy price, economic development level, foreign carbon price, new energy price index	Vector autoregressive model	2022	Study on Influencing Factors of Carbon Price and Risk Measurement of Carbon Market
Xu Yang, Xianzhao Liu	economic, population, energy, technology, policy, land and opening-up level	The STIRPAT extended model, PLS-SEM	2022	Path analysis and mediating effects of influencing factors of land use carbon emissions in Chang-Zhu-Tan urban agglomeration
Chunrui Song, Jun Yang, et al.	Economic aggregate (GRE), land scale (LS), and land intensity (LI0	pearman correlation analysis and factor detection of Geodetector.	2022	Response characteristics and influencing factors of carbon emissions and land surface temperature in Guangdong Province, China
R Dietmar Muller, Ben Mather, et al.	Solid Earth outgassing, high-speed plate tectonics, deep-sea carbonate sediments emerged	Thermodynamic modelling	2022	Evolution of Earth's tectonic carbon conveyor belt

Lv Jingyi, Fan Xinya, Wu Haonan	Energy price, international carbon asset price, economic development level and traditional financial market	Based on Sobol method, nonparametric model is established by Gaussian process regression	2021	Parameter Sensitivity Analysis of Influencing Factors of Carbon Emission Price in China
Li Ruozhu	Foreign crude oil prices, exchange rate of Euro against RMB, Shanghai Interbank Offered Rate, Shanghai and Shenzhen 300 and CER prices, foreign coal prices, exchange rate of USD against RMB and Standard & Poor's Index.	Lasso method	2020	Study on Influencing Factors of Regional Carbon Emission Trading Price in China —— Based on Lasso Method

According to (Table 1) the summary of the current research on the influencing factors of carbon trading price at home and abroad, combined with theoretical knowledge such as economics and environmental science. From the perspectives of supply, demand and market, the influencing factors of emission rights trading price are analyzed, and the indicators that have a great influence on carbon trading price are selected respectively. Considering the factors such as data availability, this study summarizes the following four influencing factors and their specific indicators.

3.1.1. Macroeconomy

The level of economic development directly affects social demand and consumption. Carbon trading activities cannot be carried out without market economy, and macroeconomic fluctuations will inevitably affect the rise and fall of carbon trading prices. [8] a large number of empty containers will be idle, the demand for carbon emissions will decrease, and carbon price transactions will fall, and vice versa.

In this study, the carbon efficiency of SSE 180, which has the closest relationship between the domestic economy and the green financial carbon trading market, is selected as a reflection of the carbon management benefits of domestic enterprises, and its index meaning is to reflect the performance of low-carbon emission companies based on the carbon footprint data of listed companies. For domestic and international macro-economy, the ups and downs of Shanghai Composite Index and Dow Jones Industrial Average are selected as the challenges of domestic and international macro-economy to the domestic carbon trading market.

3.1.2. Energy price

One of the important sources of CO2 emission is the combustion of fossil fuels. On the one hand, the carbon emission trading market changes the consumption of fossil fuels by ships through cost control. When the energy price rises, enterprises have to reduce the purchase and use of energy, thus reducing the demand for carbon emission rights, which eventually leads to the decline of carbon emission prices. On the other hand, shipping enterprises can improve energy utilization rate, reduce fossil energy transactions, and sell carbon emission rights to gain benefits, thus alleviating the pressure of enterprises with large fossil fuel consumption.

[10] As the port with the largest coal throughput in Australia, Newcastle chooses its coal price as an important performance of international coal price and a typical representative index of domestic coal price.

3.1.3. Climate and environment

One of the leading factors that affect the carbon transaction price in the climate environment is temperature. When the environment is extremely hot or extremely cold, the energy demand rises and the carbon dioxide emissions increase, so the carbon transaction price also changes. The content of greenhouse gases in the air directly determines the formulation of carbon trading price. The air quality

index (AQI) shows the content of main pollutants in the air, and also describes the data of the daily maximum temperature to the minimum temperature.

3.1.4. International market

The demand subject of CER approval is the enterprises with carbon emission rights gap in developed countries, while the supply side is the enterprises with clean emission reduction mechanism in developing countries. The gap between supply and demand directly affects the domestic carbon trading price, and CER is an important indicator to measure this gap. On the other hand, due to the differences between domestic and foreign markets, exchange rate, as a value indicator to measure different currencies, directly affects the price difference between domestic and foreign carbon transactions, and traders in the market prefer to trade in markets with more advantageous prices. The above factors are as follows (Table 2).

Table 2. Detailed indicator system

influencing factor	Indicator name	Variable code	data source
dependent variable	Carbon price	DealPrice/ yuan	Carbon trading network
macro-economy	Carbon efficiency index	TanChange	CSI Index
	Shanghai composite index rises and falls	SHChange/%	Djinn Finance
	Dow Jones index rises and falls	DJChange/%	Djinn Finance
Energy price	Texas crude oil price	WTI/ (USD barrel)	Djinn Finance
	Ektian hot gas price	ECO/ (USD barrel)	Djinn Finance
	Newcastle coal price	NEWC/ (USD barrel)	Djinn Finance
	Natural gas price	Gas/ (yuan t-1)	Jintou net
	Coal price	Goal/ (yuan t-1)	sequence
Climate environment	Daily maximum temperature	HTem/℃	Weather network
	Daily minimum temperature	LTem/℃	Weather network
	Air quality index	AQI	CSMAR network
international market	Certified emission reduction	CER/ euro	European energy exchange
	Rate of exchange rate change	ExChange/%	Djinn Finance

3.2. Data processing and index screening

As for the carbon trading price, due to the different trading dates in domestic and foreign markets, this study excludes the influence of rest days and holidays, and obtains the data of Yangshan Port's effective trading day in the carbon trading market for 357d days. In order to avoid the influence of exchange rate, the monetary unit of measurement is unified, and the original data is multiplied by the exchange rate to calculate the foreign crude oil, foreign natural gas price, foreign coal price and approved emission reduction respectively. Finally, aiming at the index of extreme weather, it is generally recognized that the highest temperature on that day is above 35℃ and the lowest temperature on that day is below 0℃, which is called low temperature. Set a dummy variable, when the temperature is higher than 35℃ or lower than 0℃, set it to 1, and set the rest to 0.

Before Lasso regression variables are screened, because the above variables are all time series data, if the series is non-stationary, the problem of pseudo-regression may arise by directly establishing regression model, so it is necessary to test the stationarity of the series' first. The results of stationarity test are shown in Table 3: certified emission reduction, Texas crude oil price and Newcastle coal price are not stable, while other variables are stable.

Table 3. Results of Stationarity Test and Variable Selection

variable	Test statistics	P value	Stationarity	Lasso statistics	result
Carbon price	-1.888	0.030	stable	—	—
Carbon efficiency index	-2.951	0.002	stable	-0.020	reserve
Shanghai composite index rises and falls	-3.366	0.000	stable	0.000	eliminate
Dow Jones index rises and falls	-4.184	0.000	stable	0.000	eliminate
Texas crude oil price	0.15	0.560	Nonstationary	—	—
Growth rate of Texas crude oil	-0.665	0.253	stable	0.000	eliminate
Eck natural gas price	-2.049	0.020	stable	-0.121	reserve
Newcastle coal price	-0.787	0.216	Nonstationary	0.000	eliminate
Newcastle coal growth rate	-3.578	0.000	stable	—	—
Natural gas price	-1.827	0.034	stable	-0.014	reserve
Coal price	-1.979	0.024	stable	-0.248	reserve
extreme weather	—	—	—	0.109	reserve
Air quality index	-4.721	0.000	stable	0.027	reserve
Certified emission reduction price	-0.006	0.498	Nonstationary	—	—
Certified emission reduction price growth rate	-3.076	0.001	stable	0.002	reserve
Rate of exchange rate change	-2.028	0.021	stable	0.026	reserve

After Newcastle coal price is converted into growth rate, it is tested again, and the transformed sequence is stable. At this time, the approved emission reduction growth rate, Texas crude oil price growth rate and Newcastle coal price growth rate are named CER-R, WTI-R and NEWC-R respectively. At this time, all variables are stationary series, so Lasso regression model can be established to screen variables.

After the stationarity test, let's use Lasso regression to select variables. The coefficients β0 and βj of Lasso are obtained by solving the minimum value of the following formula:

$$\sum_{i=1}^{n}(y_i - \beta_0 \sum_{j=1}^{p} \beta_j x_{ij})^2 + \lambda \sum_{j=1}^{p} |\beta_j| = RSS + \lambda \sum_{j=1}^{p} |\beta_j| \quad (1)$$

Among them, yi is the dependent variable, Xiji is the variable to be selected, and it is the adjustment parameter. The main principle of Lasso is that by setting the limited area of the penalty term, λ will compress βj to 0 when the adjustment parameter increases continuously, and βj will be compressed to 0 when the adjustment parameter reaches a certain level, thus completing the selection of variables and making important variables stand out. At the same time, under the limitation of control size, the coefficient that minimizes the sum of squares of residuals is found as much as possible. The selection of adjustment parameters can be obtained by cross-validation. The main idea is that by randomly dividing the observation set into k groups with basically the same size, the first group is the verification set, and the rest is the h-1 group fitting model, the whole process will get H test errors: MSE series values, calculate their corresponding cross-validation errors, and then select the parameter with the smallest CV, so as to get the optimal adjustment parameters and complete the fitting of the model. According to the above Lasso principle, the initially selected indicators are standardized to avoid the dimension affecting the size of the penalty item. According to the two parameters of Lasso in Lars package of R language, the variables are selected, and the most suitable

adjustment parameters are selected by 10-segment crossover method. It is found that CVm0=0.903 is the minimum cross-validation error.λ $\sum_{i=1}^{p}|\beta_i|$ λλ.

According to the principle of minimum angle regression for collinearity problem, the variables are compressed, and the results are shown in Table 3, in which the coefficients of Shanghai Composite Index, Dow Jones Index, Texas crude oil growth rate and Newcastle coal price growth rate are compressed to zero, and four variables are excluded in total, leaving eight important scalars.

Let x0 be the value of period k of a monotone non-negative original time series. First of all, it is necessary to weaken the randomness of the original sequence by sequential accumulation to get the sequence X ", and establish the following first-order linear differential equation for X:

$$〚\boldsymbol{dX}〛\text{^}((\mathbf{1}))/\boldsymbol{dt} + \boldsymbol{\alpha X}\text{^}((\mathbf{1})) = \boldsymbol{\mu} \quad (2)$$

Get the grey model GM (1,1) and solve the predicted value:

$$X(K+1)=(x(0)-u/a)e\text{^}-ak+\mu/\alpha \quad (3)$$

In the process of model prediction, accumulation processing is carried out, so if the real prediction value needs to be obtained, it needs to be accumulated and subtracted, and the data X(k+1) obtained by GM (1 1,1) model is accumulated and subtracted.

$$X(k+1)=(e\text{^}-ak-1)|X(n)-\mu,\alpha|*e\text{^}-(\alpha k) \quad (4)$$

The prediction results of the sequence can be obtained from the reaching step, but the accuracy of the prediction results needs to be measured by comparing the precision table of the posterior variance model. The prediction accuracy of the model is judged by calculating the ratio C (posterior difference ratio) of the variance of the original sequence X and the residual. The smaller the C, the smaller the difference between the predicted value and the actual value. According to the discriminant table of posterior difference test, when the c value is less than 0.350, it shows that the model fitting effect is good; When the value of C is between (0.350-0.5001), the model fitting effect is "qualified"; When the value of C is between (0.500-0.6501), the fitting effect of the model is "basically qualified"; C value > 0.650, indicating that the fitting effect is poor), and other methods need to be used for prediction. In order to avoid the error influence of random factors on the grey forecasting model as much as possible, this study adopts different forecasting processes for different explanatory variables, and directly adopts the grey forecasting model for air quality index, domestic coal price and natural gas price.

4. Forecast Analysis

When the problem of randomness in the input layer of the traditional BP neural network is solved in the forecasting process, the relationship between the input and output of neurons can be established through the simulation process of the traditional BP neural network model, and the complex relationship between the important influencing factors in the carbon emission rights market and the price of carbon emission rights can be simulated. The specific implementation process of BP neural network is shown in Figure 1.

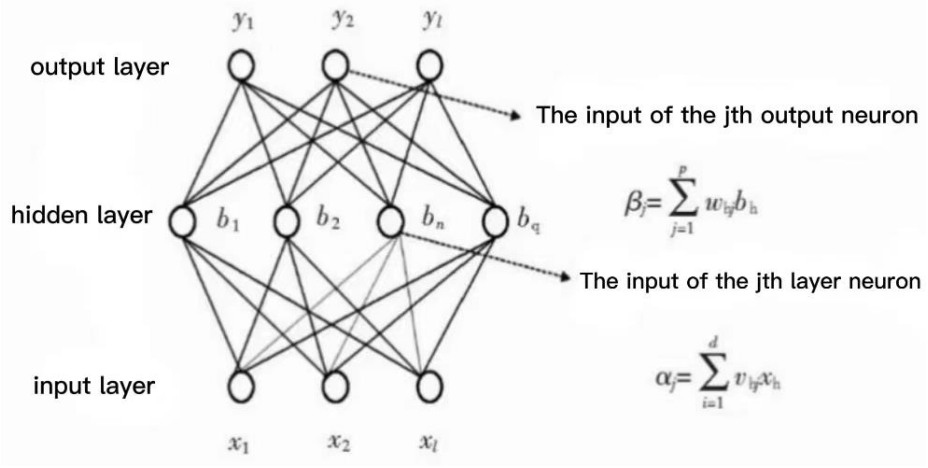


Figure 1. Schematic diagram of BP neural network algorithm

4.1. Data input

In the range of (0,1), the connection weight wij and the threshold θij of all nodes in the network are randomly initialized, and the standardized samples of important influencing factors and the carbon emission trading price Yk are read in.X_k

4.2. Model training

According to the known parameters, the current carbon emission trading price Yk is calculated, and the gradient term gi of the output layer neuron and the error signal of the hidden layer neuron node are calculated, and the error is propagated back, and the weights and thresholds are corrected.

4.3. Output predicted value

Calculate the error and repeat the above steps until the required error range is reached and output.

On the basis of data standardization, the neural network model is trained by using the existing sample data, and its parameters are set as error parameter 10*(-7), learning times 10000, and the number of neurons is 8 data with variables that significantly affect the price change of carbon trading. After 480 iterations, it converges to 82.550, and the prediction model is obtained. Before using the model to forecast, it is necessary to evaluate the forecasting ability of the model.

In order to evaluate the prediction accuracy of the model, it is necessary to quantify the error. The average absolute relative error (MAPE) not only considers the error between the predicted value and the real value, but also considers the ratio between the error and the real value. It is generally believed that MAPE is less than 10% and the model fitting accuracy is high.

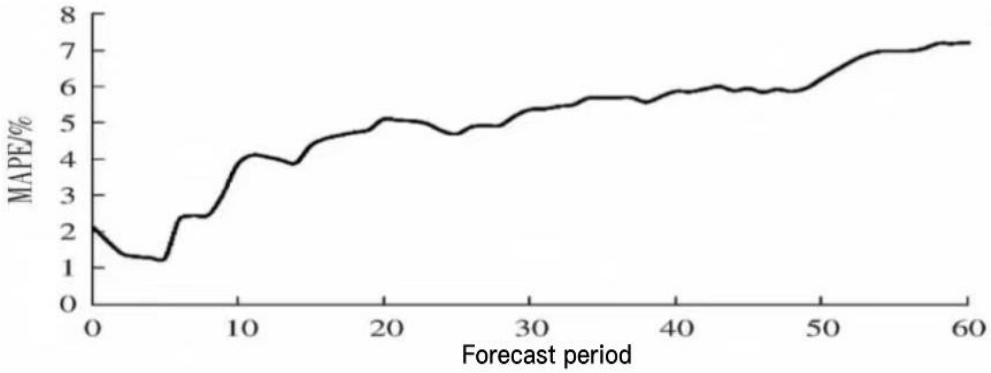


Figure 2. Average absolute percentage error of prediction model

As can be seen from Figure 2, the error of forecasting model method shows a gradually increasing trend with the increase of forecasting period. Within 10 periods (the first period is 7 working days), the MAPE is less than 4%, and the prediction effect is good. For a long time, MAPE is below 8%, and

the medium and long-term prediction effect is good. The next 10 periods are predicted according to the prediction model, and the specific results are as follows (Table 4 and Figure 3).

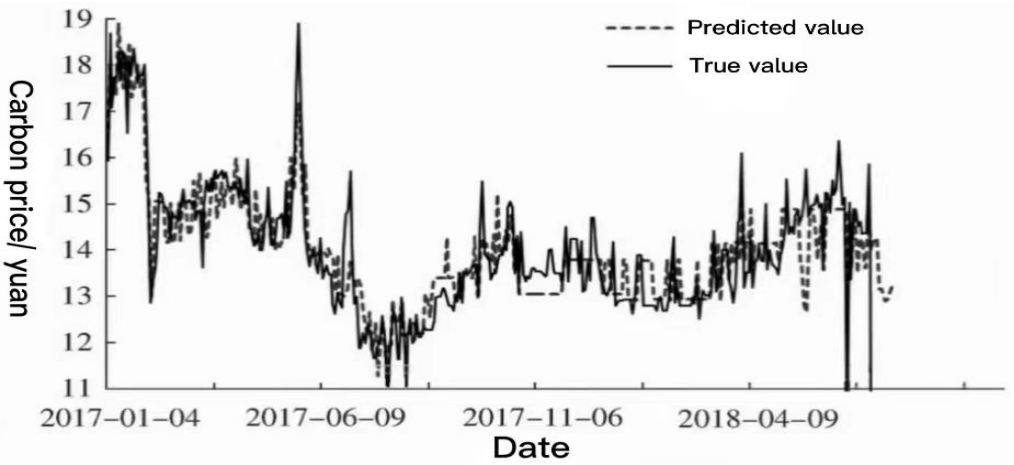


Figure 3. Comparison diagram between predicted value and true value of BP neural network

Table 4. Prediction results of BP neural network

period	2017-01-04 to 01-12	2017-03-06 to 03-14	From June 1, 2017 to June 9, 2017	2017-08-02 to 08-10	2017-11-06 to 11-14	2017-12-04 to 12-12	2018-01-04 to 09-12	From February 1, 2018 to February 9, 2018	2018-03-05 to 03-13	2018-04-09 to 04-17
predicted value	14.19	14.22	14.28	13.16	13.16	13.03	12.90	12.95	13.10	13.25

As can be seen from Figure 3, although the fitting effect of BP neural network prediction model on carbon trading price is not good in a few areas, the accuracy is relatively low, but the prediction can accurately capture the price fluctuation points and can fit the data fluctuation trend and fluctuation.

4.4. Sensitivity analysis

Based on path analysis, this paper discusses the influence mechanism of carbon trading market structure influenced by carbon price on China's carbon market intensity, and analyzes the sensitivity of carbon consumption structure changes of port enterprises in China to carbon intensity by using FAST.

Let the independent variables X1, X2, X3, X4, the dependent variables Y1, Y2, Y3, rij be the correlation coefficient between Xi and the dependent variable y, and Pij be the partial correlation coefficient after standardization between xi and the dependent variable y.

Table 5. Path analysis of the influence of variables on carbon intensity

independent variable	Total influence	Direct path	Indirect path				
			X1	X2	X3	X4	Total indirect effect
X1	0.670	0.89	—	0.09	-0.475	0.164	-0.221
X2	0.279	0.72	0.111	—	-0.329	-0.223	-0.441
X3	-0.456	0.68	-0.623	-0.348	—	-0.164	-1.135
X4	-0.630	-0.79	-0.185	0.202	0.141	—	0.159

According to the calculation results in Table 5, the total influence of each independent variable is approximately equal to the sum of direct path and total indirect path, which is consistent with the results of path theory, indicating that the results of this study are reliable. T [3] (hydropower, wind power, nuclear power, etc.) is the main factor to inhibit the growth of carbon intensity. Carbon intensity is sensitive to the proportion of carbon consumption, and the most obvious effect of reducing carbon

intensity can be achieved when the proportion of coal consumption is replaced by the proportion of other energy sources per unit under the premise of the same total amount.

5. Effect Evaluation and Suggestions

Because the carbon price of port enterprises is getting higher and higher, they have to respond to the call of national emission reduction, and China's influence on the carbon emission rights of port enterprises has a vital impact on their carbon trading market. At this time, it is necessary to deal with China's carbon emission rights to evaluate the effect of the port carbon trading market.

5.1. Effect evaluation

[2] If a market wants to trade products, it must need enough potential market traders to participate in market trading activities. Only enough potential traders can make the market develop more maturely and efficiently. Based on this, this paper selects the total amount of carbon trading, the total amount of carbon trading, the average transaction price, the volume of CCER (national certified voluntary carbon emission reduction) and the quota as evaluation indicators. The first three indicators can directly reflect whether the pilot carbon market has attracted more potential traders and the change of market scale; The CCER volume, quota volume and total transaction volume are compared and analyzed to show the activity and operation status of the pilot carbon market and the market participation of potential traders.

In 2018, 2019 and 2020, the total amount of carbon transactions, total transaction amount, average transaction price, CCER volume, transaction amount, transaction price, carbon issuance quota and CCER volume data of Shanghai Port Carbon Pilot Project were collected from China Carbon Trading Network, Shanghai Port Carbon Emission Point, Shanghai Environment and Energy Exchange WeChat official account and Shenzhen Carbon Emission Exchange WeChat official account.

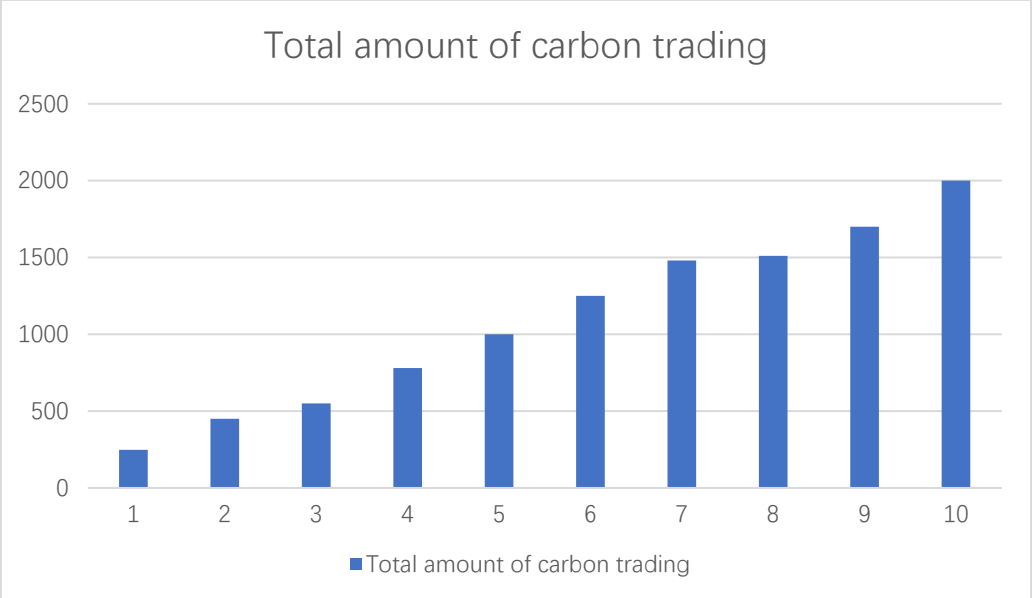


Figure 4. Predicts the 10-phase port carbon trading.

As can be seen from Figure 4, the total amount of carbon trading continues to increase, and the total amount of carbon trading shows an upward trend, with more enterprises participating in trading and an increase in market size; [1] The port carbon market has become a smaller carbon market in the pilot carbon market because of the low proportion of heavy industry and fewer industries and enterprises included in the carbon market. From the model forecast, we can get the price forecast of carbon trading in the next 10 ports, and the total amount of carbon trading will continue to rise, which will promote energy conservation and emission reduction in ports and promote the construction of "zero carbon ports".

5.2. Suggestions

In order to promote the development of carbon emissions trading market in the port area, combined with the above model prediction and analysis, we should optimize the energy consumption structure, focus on reducing the proportion of coal consumption by port enterprises and increasing other clean energy consumption, [4].

5.2.1. Increase the proportion of low-carbon transportation equipment.

Control the application of high energy consumption and high emission equipment in ports from the source, increase the proportion of equipment powered by electricity and natural gas, and reduce the consumption of fossil energy. Promote the application of LNG on ships, promote a new generation of low-carbon port-based ships, comprehensively apply new energy-saving technologies for ships, and improve the use of clean energy and renewable energy.

Expand the popularization and application of climate-friendly technologies in ports, broaden the funding channels for ports to cope with climate change, and improve the statistical verification norms for port energy consumption and emissions monitoring.

5.2.2. Construction of ocean-port carbon sink trading platform

Ocean-port carbon sink trading information plays an increasingly significant role in its development, and building a port carbon sink trading market information platform will promote China's low-carbon innovation and development to a higher quality. Under the joint influence of macro factors, internal factors, external factors and boosting factors, China can build a port-related carbon sink trading information platform based on the existing superior resources, combine port carbon sink information with marine carbon sink information into the whole chain of its marine industrial chain and low-carbon innovation and development, and integrate marine carbon sink information into port services, sharing and other functions to meet the creative needs and coordinated development of co-creators, thus giving full play to the ability of the information platform to create value.

6. Summary

Considering macro-economy, energy price, climate and environment and international market, the index system of carbon trading market is established. By using Lasso regression to objectively screen out the important influencing factors, the BP neural network model is established, and it is concluded that the total amount of port carbon transactions will continue to increase in the next 10 periods, and the total amount of carbon transactions will show an upward trend. After sensitivity analysis of the influencing factors, China's carbon emission trading market is mainly affected by coal prices. Therefore, we focus on reducing the proportion of coal consumption by port enterprises and increasing other clean energy consumption, and put forward the corresponding construction path of "zero-carbon port", and combine with the marine carbon sink trading platform to promote the port's emission reduction by using marine biological carbon sinks.

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