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Research on the Impact of Carbon Market Trading on Emission Reduction Efficiency

-- TOPSIS based Evaluation of Emission Reduction Efficiency of Domestic Pilot Carbon Market

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Abstract

With the challenges brought by global climate change, the concept of green development has gradually attracted people's attention. In order to explore the influencing factors of domestic carbon market transaction price, this paper analyzes the main influencing factors of carbon emission trading price through recursive neural network algorithm in deep learning and establishes a prediction model. The carbon price, energy, economy, policy regulation and other data of domestic pilot carbon market are used to predict the carbon emission trading price, and the data are divided into training set and test set to test the accuracy of the model. In order to further explore the impact of domestic CCER projects on carbon market emission reduction efficiency, this paper uses entropy weight method and TOPSIS to establish an evaluation model of carbon trading market emission reduction performance from three perspectives of environment, policy and economy, and makes a comparative analysis of emission reduction efficiency of each market, so as to put forward further optimization suggestions for the improvement and future development of domestic pilot carbon trading market trading system.

Keywords

Carbon Emission Trading Market; CCER Project; Recurrent Neural Network Model; Carbon Quota Control.

1. Research Background

1.1. Global Warming has Attracted International Attention.

With the opening of the machine age by the industrial revolution, social productive forces began to develop at a high speed, and the material resources that people could obtain were greatly enriched. With the rapid development of productivity, the demand for carbon-containing energy is increasing. For a long time, people have always ignored the impact of colorless and odorless carbon dioxide on our lives. However, with the development of science, we have found that the greenhouse gases produced by our use of carbon energy have led to global warming, also known as the "greenhouse effect" [1].

In recent years, the rise of sea level, the fusion of glaciers and the decrease of biodiversity have made people gradually realize the impact of greenhouse effect on our lives, and the climate problem has gradually become a common challenge for human beings all over the world. In order to meet the challenge of global warming, reducing global carbon dioxide emissions has become the most feasible method at present. For this reason, various countries and organizations in the world have reached exchanges and communication on climate change and reached some agreements [2]. The signing of the United Nations Framework Convention on Climate Change in 1992 marked the first time that controlling carbon emissions became an international consensus. In the Kyoto Protocol in 1997, it was the first time to restrict

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greenhouse gas emissions in the form of laws and regulations, and it was also the first time to regard carbon emissions as a right, allowing carbon emission quotas to circulate and trade between different countries, aiming at guiding a trend of coordinating national resources to solve ecological problems through market means. [3].

1.2. Carbon Emission Reduction Mechanism

At present, there are two kinds of carbon emission reduction mechanisms recognized internationally, one is the cooperation between countries based on emission reduction projects, such as the scenario development mechanism (CDM) between developed countries and developing countries and the joint implementation mechanism (JI) between developed countries, and the other is the emission trading mechanism (ETS) based on the carbon emission trading market. Under the emissions trading mechanism, carbon emission rights mainly reflect its financial attributes. Based on carbon quotas, the overall carbon emissions are controlled through the adjustment of carbon price mechanism. Because of its high flexibility, the emissions trading mechanism has strong adaptability to the market and good implementation effect.

1.3. Development of Domestic Carbon Market

As the world's largest energy consumption country, China has been actively undertaking social responsibilities in the field of carbon emission reduction. In 2013, eight pilot carbon emission trading markets were established in China. In 2020, General Secretary Xi Jinping put forward the targets of "carbon neutrality" in 2035 and "peak carbon dioxide emissions" in 2060, which showed China's determination to reduce carbon.

At present, the domestic carbon emission trading market is still in the development stage. Due to the limitation of the allocation method of national quotas and the floating ratio of carbon price, the flexibility is poor, and the carbon price cannot truly reflect the marginal emission reduction cost of enterprises, which leads to the waste of carbon quotas and low emission reduction efficiency. At the same time, due to the financial nature of the carbon market, its fluctuation is also affected by many factors, such as energy prices, climate conditions, policy regulations and economic conditions. Due to the complexity and variability of the carbon market, the management of carbon assets has also become an important business for some enterprises.

1.4. China Certified Emission Reduction (CCER Project)

In 2012, the National Development and Reform Commission put forward the concept of voluntary emission reduction for the first time, and explained its trading process, marking the establishment of the domestic CCER system. It is defined as the quantitative verification of the effect of domestic emission reduction projects, and registered in the carbon exchange as the voluntary emission reduction certification. [4]. Since 2014, the first batch of CCER projects in China have been put on record, and the mechanism of voluntary emission reduction is verified, that is, enterprises can transfer idle carbon quotas to other emission control enterprises in market transactions after achieving emission reduction through energy-saving transformation. Through this mechanism, enterprises can be encouraged to reduce carbon emissions through technological upgrading, thus realizing economic benefits and achieving emission reduction targets.

Although CCER mechanism can encourage some enterprises to increase investment in emission reduction, the trading price of CCER quotas fluctuates greatly due to the market supply and demand mechanism, and some enterprises can develop a large number of CCER quotas every year through technological improvement, which leads to the phenomenon of oversupply of CCER quotas in the pilot market. Excess supply will lead to the decline of its price, and some enterprises will reduce the cost of carbon reduction by purchasing CCER quotas, which will lead

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to the decline of emission reduction efficiency and have a certain impact on the original quota trading mechanism in the carbon market.

In addition, due to the imprecise accounting mechanism of emission reduction and the imperfect management mechanism, the National Development and Reform Commission suspended accepting applications for CCER projects from March 2017, and the existing CCER projects that have been filed before can still participate in the transaction, which also marks the suspension of CCER projects that have been implemented in China for five years.

2. Research Significance

At present, the carbon emission brought by industrial production is still one of the main sources of carbon emission, and the control of carbon emission will certainly affect the cost of enterprises. The upgrading of carbon reduction technology can reduce the marginal emission reduction cost of enterprises and take an advantage in future competition, and enterprises themselves will realize the importance of improving the carbon asset management system. From the process of carbon reduction, the carbon reduction process of enterprises is generally divided into five links: carbon verification, technical improvement, carbon reduction route formulation, implementation and monitoring, and carbon quota purchase and payment. In this process, it is of great significance to do a good job in enterprise carbon assets and verification for the development of China's carbon market. Standardized accounting confirmation and measurement of carbon emission trading can promote the development of carbon trading market. Because China's carbon market is still in its infancy, the construction and supporting mechanisms in all aspects are not perfect. The establishment of enterprise carbon accounts, the confirmation and verification of carbon emissions, and the settlement and trading of carbon quotas all need the support of carbon accounting. Playing the accounting function can help emission control enterprises to better calculate the costs and benefits of emission reduction, formulate more reasonable emission reduction plans, and take the initiative to undertake emission reduction responsibilities, so that enterprises have the ability and willingness to carry out carbon emission reduction. The provision of carbon accounting information can reflect the technological advantages and investment intensity of enterprises in emission reduction, and investors can regard it as one of the indicators of the future development of enterprises to make rational investment decisions.

In addition, carbon trading is an emission trading mechanism based on enterprises' carbon emission decisions. Reasonable quota allocation and accurate accounting are more conducive to the establishment of trust in the carbon trading market and the flow of carbon quotas, which improves the efficiency of emission reduction through marketization. Accurate verification and identification of carbon emissions is also the basis of standardized management of carbon trading. The development and perfection of carbon market provides a platform and opportunity for enterprises to improve technology and reduce costs. In the process of carbon emission accounting, enterprises can use this as a standard to realize the optimal management of carbon assets through various means, promote the healthy and orderly development of carbon trading market, and finally achieve the national macro emission reduction goal.

3. Literature Review

Previously, scholars' research on the domestic carbon emission trading market mostly focused on the design of carbon emission trading mechanism and the evaluation of the operating efficiency of carbon market. Chen Jing (2009) constructed a carbon trading price function based on CDM trading mechanism, domestic policy measures and market mechanism, and analyzed it from quota quantity, actual emissions, transaction cost and government price-fixing mechanism, which laid the foundation for the later scholars' research. Cui Yeguang (2017) established the relationship between carbon emission control efficiency and corporate carbon information disclosure and carbon asset management through the study of carbon emission trading mechanism in Beijing-Tianjin-Hebei regional carbon market, and explored the impact of corporate carbon information disclosure and carbon asset management ability on emission reduction efficiency. Guan Lijuan (2012) took the data of Shanghai as an example, based on the shadow price model of carbon dioxide, studied the initial allocation and price mechanism of domestic carbon emission rights to provide reference for the initial pricing of carbon emission rights.

Previously, scholars' research on domestic CCER projects was mostly the analysis of specific projects at the micro level, and there was little research on the operational efficiency of CCER projects. This paper innovatively takes CCER quota price and trading volume as influencing factors, explores the impact of CCER project on the emission reduction efficiency of domestic carbon market, and discusses the possibility of restarting CCER project.

4. Analysis of Influencing Factors of Domestic Carbon Market Price

4.1. Model Construction

1) Description of time series prediction problem

The input time series is X==()∈,n represents the length of time input time series, ∈ represents the length of time series in the kth state, and ∈ represents the sequence input at time point i.$(x^1, x^2, \dots, x^N)^T x_1, x_2, \dots, x_t R^{Nxt} x^k = \left(x_1^k, x_2^k, \dots, x_t^k\right)^T R^T x_i = (x_i^1, x_i^2, \dots, x_i^N)^T R^N$

Given the current and previous values (), where. The input sequence is set to (); . () =F ((), ()) is the sequence value predicted at the next m time points, and f () is the model prediction function that this paper needs to learn through the existing data. The goal of learning is to minimize the error between the actual value () ∈ and the predicted value (). $y_1, y_2, \dots, y_t \in R^N y_i \in R x_1, x_2, \dots, x_t x_i \in$ $R^N \hat{y}_{t+1}, \hat{y}_{t+2}, \dots, \hat{y}_{t+m} y_1, y_2, \dots, y_t x_1, x_2, \dots, x_t y_{t+1}, y_{t+2}, \dots, y_{t+m} R^m \hat{y}_{t+1}, \hat{y}_{t+2}, \dots, \hat{y}_{t+m}$

2) XGBoost model construction

XGBoost model is one of the Boosting algorithms. The idea of Boosting algorithm is to integrate many weak classifiers to form a strong classifier. Because XGBoost is a lifting tree model, it integrates many tree models to form a strong classifier. [5]. XGBoost provides higher efficiency, accuracy and scalability than RF. It supports fitting various objective functions, including regression, classification and ranking. XGBoost is more flexible because optimization is performed on an extended set of super parameters.

XGBoost objective function is defined as:

Obj=+() (1)

$$\sum_{i}^{n} l(y_i, \hat{y}_i) \sum_{k=1}^{k} \Omega f_k$$

According to Equation (1), the objective function consists of two parts, one part is used to measure the difference between the predicted value and the real value, and the other part is a regularization term. As mentioned above, XGBoost is an Ensemble machine learning method based on Boosting, and the newly generated predictor is to fit the residual of the last prediction, that is, after the T predictor is generated, the predicted value can be written as Equation (2):

$\hat{y}_i^{(t)}$=+ () (2)

$$\hat{y}_i^{(t-1)} f_t x_i$$

The objective function can be rewritten as Equation (3) accordingly:

$$\text{Obj}=(+())+() \tag{3}$$

$$\sum_{i}^{n} l\, y_i, \hat{y}_i^{(t-1)} f_t x_i \sum_{k=1}^{k} \Omega\, f_k$$

After that, XGBoost algorithm will search according to the second-order Taylor expansion and greedy strategy to minimize the objective function.f_t

4.2. Data Description

1) data description

This paper selects the closing price data of carbon prices in Shanghai, Tianjin and Beijing from January 1, 2010 to January 1, 2021 as the research object. The sample data is divided into two subsets: training set and test set. Among them, the sample data from January 1, 2010 to December 31, 2017 is used as the training set (accounting for nearly 60% of the total sample size), and the remaining sample data from January 1, 2017 to January 1, 2021 is used as the test set (accounting for nearly 40% of the total sample size).

Table 1. Beijing Data

variable name	maximum	minimum value	average value	standard deviation
Carbon price (EUR/ton)	76.948	46.391	55.292	10.263
Green financial index	0.793	0.516	0.669	0.108
Coal consumption (ten thousand tons)	2019.23	182.8	959.717	715.52
Crude oil consumption (ten thousand tons)	1034.62	821	922.77	72.482
Natural gas consumption (100 million cubic meters)	189.4	98.81	151.934	34.815
Coal price index (EUR/ton)	0.34	0.025	0.152	0.122
Crude oil price index (EUR/barrel)	0.336	0.246	0.279	0.034
Natural gas price index (Euro/MWh)	0.493	0.309	0.42	0.069

Table 2. Data of Tianjin

variable name	maximum	minimum value	average value	standard deviation
Carbon price (EUR/ton)	29.292	11.216	19.141	7.771
Green financial index	0.353	0.249	0.294	0.036
Coal consumption (ten thousand tons)	5278.67	3766.11	4364.221	605.959
Crude oil consumption (ten thousand tons)	1759.15	1433.6	1631.296	102.93
Natural gas consumption (100 million cubic meters)	110.61	37.79	74.249	27.547
Coal price index (EUR/ton)	0.896	0.528	0.651	0.142
Crude oil price index (EUR/barrel)	0.598	0.392	0.485	0.062
Natural gas price index (Euro/MWh)	0.289	0.12	0.201	0.067

Table 3. Shanghai Data

variable name	maximum	minimum value	average value	standard deviation
Carbon price (EUR/ton)	39.838	10.064	29.77	10.693
Green financial index	0.377	0.246	0.311	0.048
Coal consumption (ten thousand tons)	5681.19	4238.28	4738.209	466.07
Crude oil consumption (ten thousand tons)	2611.76	2242.07	2464.754	140.004
Natural gas consumption (100 million cubic meters)	99.4	72.43	82.556	10.316
Coal price index (EUR/ton)	0.962	0.599	0.732	0.118
Crude oil price index (EUR/barrel)	0.886	0.684	0.759	0.063
Natural gas price index (Euro/MWh)	0.262	0.22	0.235	0.017

According to the research on the influencing factors of carbon price, this paper selects green financial indicators and energy indicators as explanatory variables, without considering indirect influencing factors such as weather and events. Specifically, three variables, crude oil price, natural gas price and coal price, are selected to measure energy prices. Three variables, crude oil consumption, natural gas consumption and coal consumption, are selected to measure energy consumption. Among them, Brent crude oil futures price (USD/barrel) is selected as the crude oil price, which is one of the major international light crude oils and the benchmark of international crude oil price; Henry Hub's natural gas futures price (USD/MWh) is selected as the natural gas price; In order to ensure that all energy prices are expressed in the same currency, the EUR/USD exchange rate of the European Central Bank is selected to convert the prices of oil, natural gas and coal into euro units. The data come from official website, National Bureau of Statistics and Wind database of various carbon market exchanges, and the statistical descriptions of each index are shown in Table 1.

2) Evaluation index

In order to evaluate the prediction ability of the model from different angles, three metrics are selected, including Directional Accuracy, DA) to measure the accuracy of directional prediction, mean absolute percentage error (MAPE) and Root Mean Square Error, RMSE) to measure the horizontal prediction ability, that is, the error between the predicted value and the real value.

$$\mathrm{DA} = \times 100\% \quad (4)$$

$$\frac{1}{m}\sum_{t=1}^{m} a(t)$$

$$\mathrm{MAPE} = \frac{1}{m}\sum_{t=1}^{m}\left|\frac{y_t-\hat{y}_t}{y_t}\right| \quad (5)$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{m}\sum_{t=1}^{m}(y_t - y_t)^2} \quad (6)$$

Where m represents the number of samples of test data, the true value of time t and the predicted value of time t. If a(t)=1, otherwise a(t)=0.$y_t\hat{y}_t(y_{t+1} - y_t)(\hat{y}_t - y_t) \geq 0$

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4.3. Result Analysis

The learning parameter of XGboost is 0.01, the maximum depth of decision tree is 10, and the number of decision subtrees is 50.

Table 4. Analysis of Forecast Capability Index of XG Boost Model

evaluation criterion	Xgboost
DA	0.4902
MAPE	0.0475
RMSE	0.3318

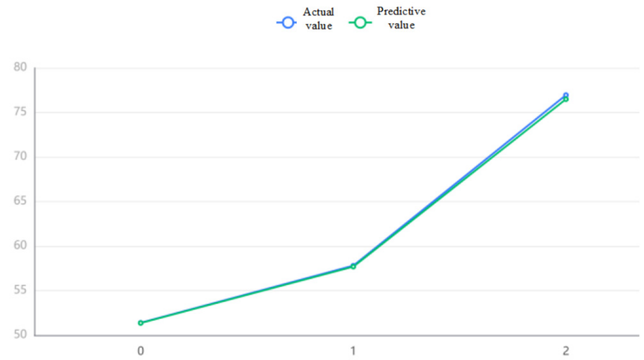

Figure 1. Forecast Chart of Beijing Carbon Emissions Trading Price

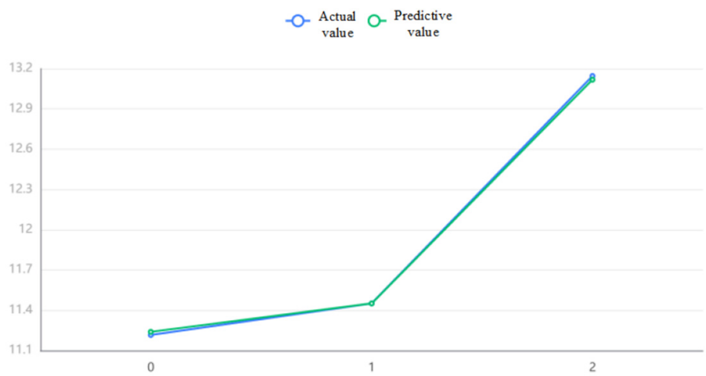

Figure 2. Tianjin carbon emission trading price forecast chart

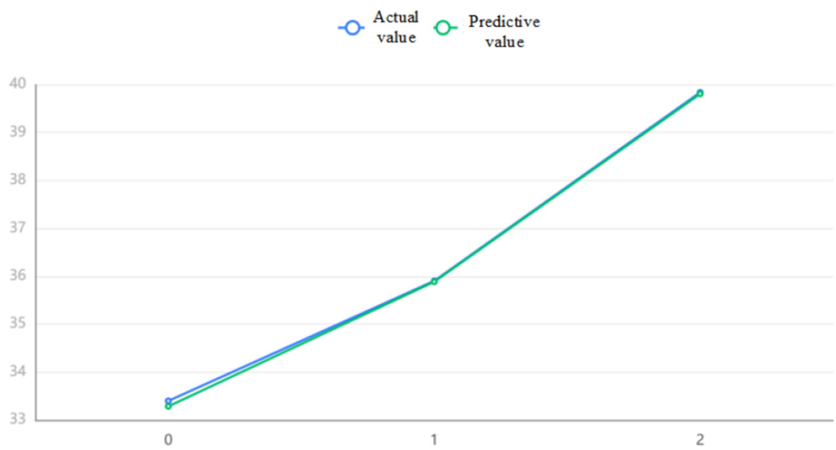

Figure 3. Shanghai carbon emission trading price forecast chart

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The results of the XBoost regression model are shown in Figure 1, Figure 2 and Figure 3. From the curve of the forecast results, it can be known that the future transaction prices of natural gas, crude oil and coal can be reasonably predicted through the seven indicators of price index and consumption of natural gas, crude oil and coal, as well as the green financial index. By comparing the prediction results obtained by cross-validation with the real values, we can see that the prediction ability of the model is good. It can be seen from the figure that the trading prices of carbon emission rights in Beijing, Tianjin and Shanghai all show an upward trend, and Tianjin started late and developed rapidly. The importance of each prediction feature in the prediction model is shown in Figure 4, Figure 5 and Figure 6. Among the influencing factors of Beijing's carbon emission trading price, the price index of fuel oil and coal is the main influencing factor, and the influence degree of natural gas price is relatively low. The mode dominated by a kind of fossil energy structure represented by Beijing is still one of the main factors affecting its carbon emission trading price and emission reduction efficiency. Natural gas price index and natural gas consumption are more important in Tianjin's forecast index characteristics, which have a great influence on the training estimation results, indicating that Tianjin's natural gas use level is higher than that of crude oil and coal, and its energy structure is more reasonable; Compared with Beijing and Tianjin, the price of Shanghai's carbon market is mainly influenced by the green finance index, which shows that the development of Shanghai's carbon finance field has a great influence on the decision mechanism of carbon emission trading price, and also provides reference for the future development of carbon finance field.

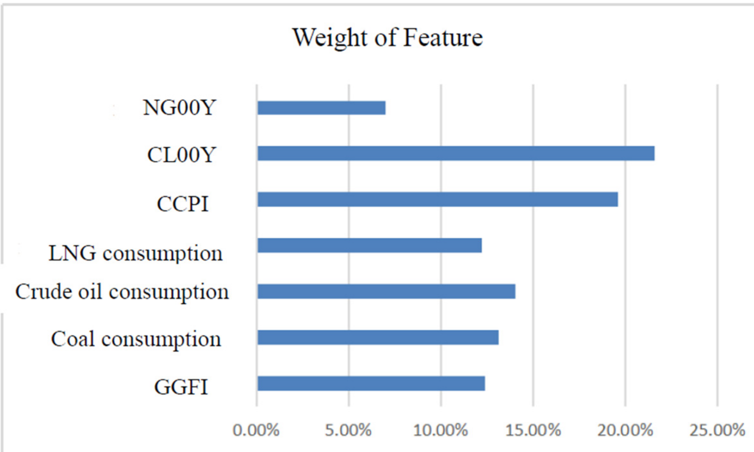

Figure 4. Importance Diagram of Forecast Features in Beijing

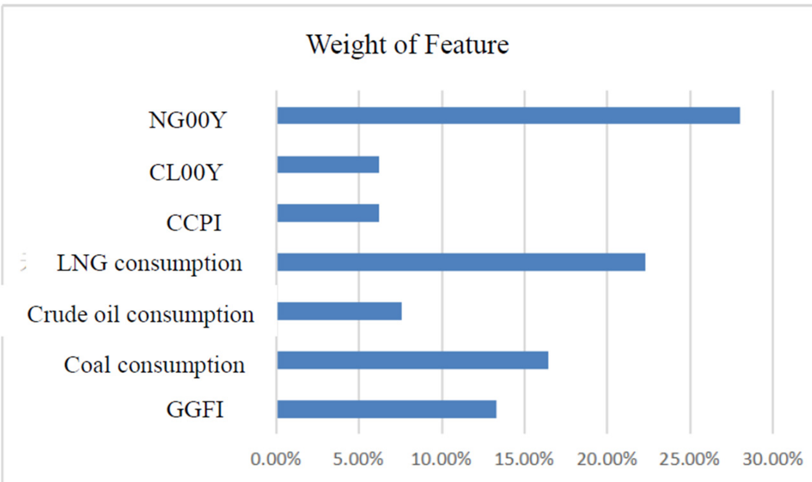

Figure 5. Importance of Forecast Characteristics in Tianjin

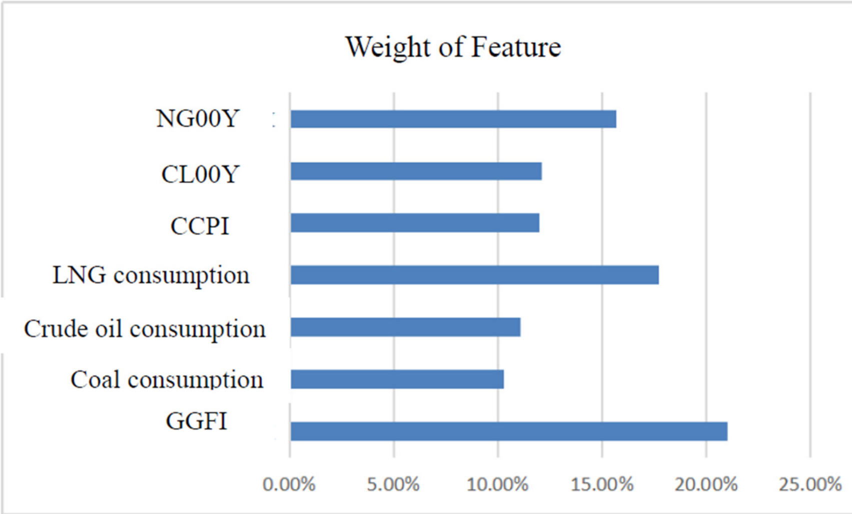

Figure 6. Importance of Forecast Characteristics in Shanghai

5. Evaluation of Domestic Carbon Market Emission Reduction Efficiency

5.1. Carbon Emissions Trading Market Performance Evaluation Index System Construction

The performance evaluation of carbon emissions trading market can be evaluated from two aspects: input and output. The input dimension can be measured by quota allocation system, emission control coverage and flexible mechanism. The output dimension can be measured from three aspects: transaction situation, emission reduction cost and environmental benefits. Considering comprehensively, when we evaluate the performance of domestic carbon market transactions, we focus on the following indicators: the total available quota, the number of enterprises participating in emission control, the maximum usage of CCER, the cumulative transaction volume, the decline rate of average transaction price and industrial CO emissions.

Through collecting and sorting, we get the data of the above five indicators in seven pilot provinces such as Beijing and Tianjin, and get the following table:

Table 5. Indicator Data of Pilot Provinces

	Maximum usage of CCER (100 million tons)	Cumulative transaction volume (10,000 tons)	Decline rate of average transaction price	Industrial CO emissions (ten thousand tons)	Total available quota (100 million tons)
Beijing	0.025	2907	0.2425	883.864	0.5
Tianjin	0.16	591	0.4590	1471.03	one point six
Guangdong	0.42	7661	0.2625	9054.43	4.2
Hubei(Province)	0.25	6309	0.0650	9260	2.5
Shanghai	0.08	3268	0.0435	1533.26	one point six
Chongqing	0.104	842	0.6771	5959.71	1.3
Shenzhen	0.03	4215	0.4547	3504.66	0.3

5.2. Data Preprocessing

(1) indicators are the same as trend processing.

By observing the data indicators, it can be found that all the indicators are extremely large except the industrial CO emissions. Therefore, we need to transform the minimal indicators into the maximal indicators. The utilization formula is as follows:

$$max - x$$

The matrix after forward conversion is:

$$X = \begin{bmatrix} 0.0000 & 0.2489 & 0.2413 & 0.5469 & 0.0897 & 0.7279 \\ 0.0002 & 0.0506 & 0.4568 & 0.5085 & 0.2872 & 0.0790 \\ 0.0004 & 0.6558 & 0.2612 & 0.0134 & 0.7539 & 0.1892 \\ 0.0003 & 0.5401 & 0.0647 & 0 & 0.4487 & 0.2834 \\ 0.0001 & 0.2798 & 0.0433 & 0.5045 & 0.2872 & 0.2378 \\ 0.0001 & 0.0721 & 0.6738 & 0.2155 & 0.2333 & 0.1368 \\ 0.0000 & 0.3608 & 0.4525 & 0.3758 & 0.0538 & 0.5220 \end{bmatrix}$$

(2) data standardization processing

In order to eliminate the influence of different dimensions and compare multiple indicators of performance evaluation under the same dimension system, it is necessary to standardize the original data. The processing method is as follows:

$$Z_{ij} = X_{ij} / \sum_{i=1}^{7} X_{ij}{}^{2} \text{i=1, 2, ...,7; j=1, 2, ..., 5}$$

The normalized matrix obtained is:

$$Z = \begin{bmatrix} 0.0470 & 0.2489 & 0.2413 & 0.5469 & 0.0897 & 0.7279 \\ 0.3006 & 0.0506 & 0.4568 & 0.5085 & 0.2872 & 0.0790 \\ 0.7892 & 0.6558 & 0.2612 & 0.0134 & 0.7539 & 0.1892 \\ 0.4697 & 0.5401 & 0.0647 & 0 & 0.4487 & 0.2834 \\ 0.1503 & 0.2798 & 0.0433 & 0.5045 & 0.2872 & 0.2378 \\ 0.1954 & 0.0721 & 0.6738 & 0.2155 & 0.2333 & 0.1368 \\ 0.0564 & 0.3608 & 0.4525 & 0.3758 & 0.0538 & 0.5220 \end{bmatrix}$$

5.3. Topsis Model based on Entropy Weight Method

Entropy weight method is an objective weighting method, which weights each index according to the difference of index mark values, thus objectively obtaining the corresponding weight of each index. Topsis method, also known as the distance method of superior and inferior solutions, evaluates the superior and inferior grades of each sample by calculating the degree of approximation to the ideal solution. Using entropy weight method to objectively weight, and then ranking according to Topsis method, we can evaluate the performance of carbon market transactions in seven pilot provinces in China relatively perfectly.

(1) using entropy weight method to empower.

Calculate the entropy value of the index, and the formula is as follows:

$$e_j = -\frac{1}{\ln(n)} * \sum_{i=1}^{n} (p_i * \ln(p_i)) \tag{7}$$

Calculate the corresponding information utility value and weight:

$$d_j = 1 - e_j \tag{8}$$

$$w_j = \frac{d_j}{\sum_{j=1}^{n} d_j} \tag{9}$$

The weights corresponding to the six indicators calculated by MATLAB are as follows:

$$w_j = (0.2080 \quad 0.1436 \quad 0.1523 \quad 0.2124 \quad 0.1496 \quad 0.1341)$$

(2) Calculate the distance from the optimal solution and the worst solution.

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Determine the sum of the optimal vector and the worst vector, where it is the maximum normalized value of the same evaluation index and the minimum normalized value of the same evaluation index.$Z^+Z^-Z^+Z^-$

$$Z^+ = (0.7892,0.6558,0.6738,0.5469,0.7539,0.5220)$$

$$Z^- = (0.0564,0.0506,0.0647,0,0.0538,0.0790)$$

(3) Calculate the score and sort it.

Calculate the weighted Euclidean distance between the seven pilot cities and the ideal solution and negative ideal solution and the relative closeness to the ideal solution. The formula is as follows

$$D_i^+ = \sqrt{\sum_{j=0}^{5} w_j[Max(X_j) - X_{ij}]^2} \quad (10)$$

$$D_i^- = \sqrt{\sum_{j=0}^{5} w_j[Min(X_j) - X_{ij}]^2} \quad (11)$$

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \text{i=1, 2, ...,7} \quad (12)$$

The results are shown in Table 6:

Table 6. Score Table

Pilot cities	score	Normalized score	sort
Beijing	0.1436	0.1957	three
Tianjin	0.1398	0.1436	one
Guangdong	0.1957	0.1422	four
Hubei(Province)	0.1422	0.1398	2
Shanghai	0.1216	0.1335	seven
Chongqing	0.1237	0.1237	six
Shenzhen	0.1335	0.1216	five

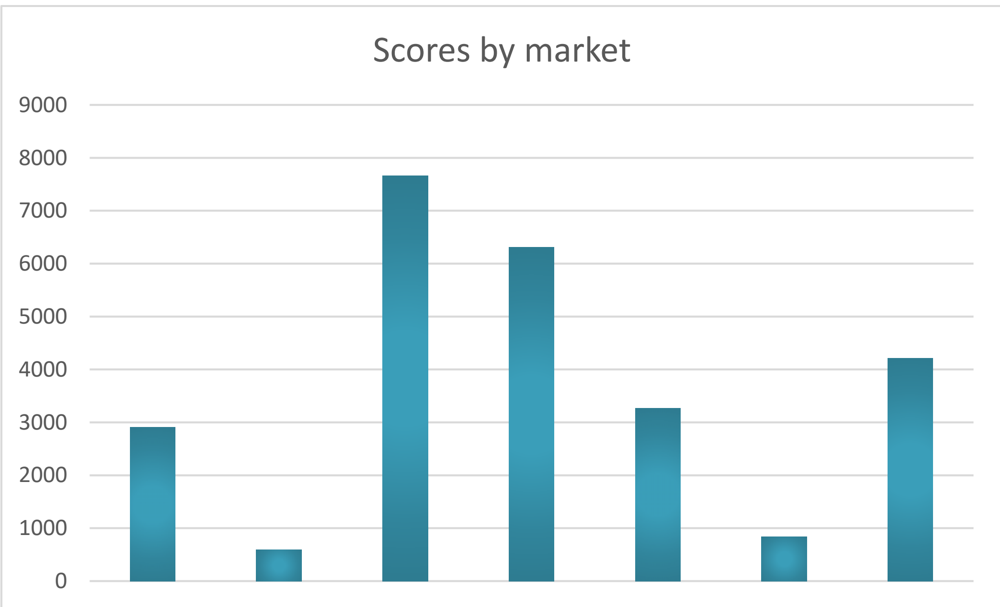

Figure 7. Score of each market

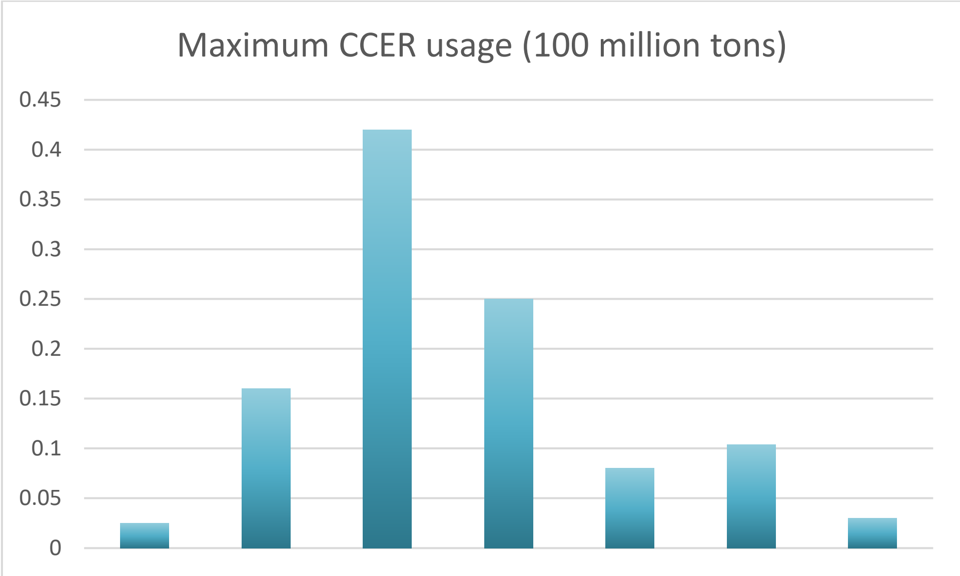

Figure 8. Maximum usage of CCER in each pilot city

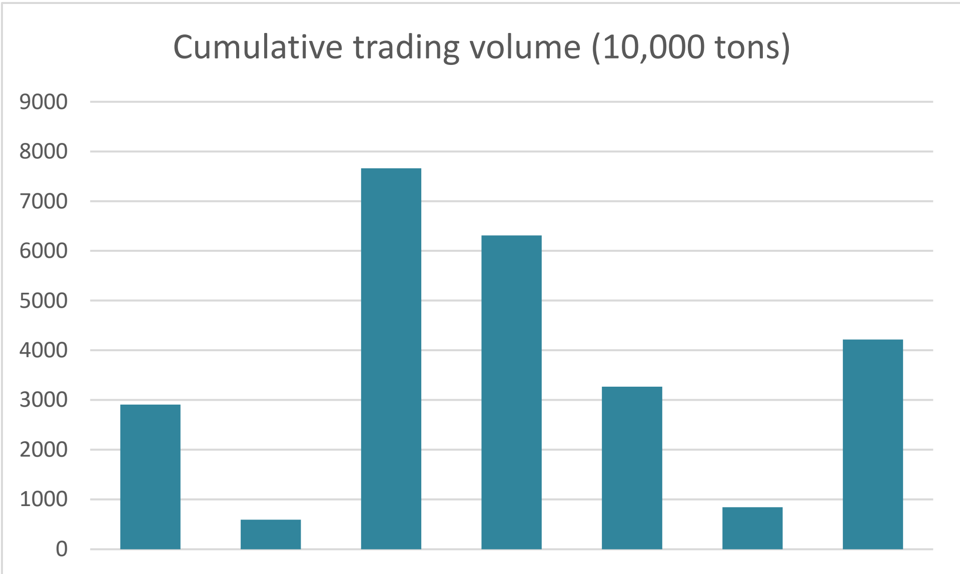

Figure 9. Cumulative transaction volume of each pilot city (10,000 tons)

Through the combination of entropy weight method and Topsis method, we forward and standardize the original data, but each index is not objectively weighted by entropy weight method. The ranking results make full use of the original data information, and can quantitatively reflect the performance of carbon markets in different pilot cities, which is more intuitive and reliable.

From the above results, we can draw the following conclusions: among the six indicators, the maximum usage of CCER, the total available quota, the number of enterprises participating in emission control, the cumulative transaction volume, the decline rate of average transaction price and industrial CO emissions, the maximum usage of CCER has the greatest impact on performance evaluation, followed by industrial CO emissions, and the number of enterprises participating in emission control has the least impact on performance evaluation. By observing the scores calculated by the distance method of superior and inferior solutions, it can be concluded that there is little difference in the scores of each pilot carbon market, among which Tianjin, Hubei and Beijing rank in the top three, while Chongqing ranks in the bottom.

6. Conclusion and Recommendations

6.1. Conclusion

In order to explore the formation mechanism and influencing factors of carbon emission trading market price, this paper analyzes the influencing factors of carbon emission trading market price through recursive neural network model and establishes a carbon price prediction model. It is concluded that regional green finance index and coal consumption have great influence on carbon emission trading price, while energy prices such as coal and natural gas have little influence on carbon emission trading price.

In order to compare the emission reduction efficiency of seven pilot carbon markets in China, this paper selects the cumulative trading volume, average market price, CCER offset quota and other indicators to build an evaluation system for emission reduction efficiency of carbon markets, and analyzes and compares the emission reduction performance of each market by using entropy weight method and TOPSIS. Finally, it is concluded that the cumulative trading volume of carbon quotas and industrial carbon emissions have great influence on the overall emission reduction efficiency of the carbon market, and Guangdong and Hubei have performed well in the operation mechanism and emission reduction efficiency of the carbon emission trading market.

6.2. Suggestions on the Development of Domestic Carbon Market

1) Accelerate the transformation of energy structure.

At present, the carbon emissions in the field of energy production still account for a large proportion of the total social emissions. In order to promote the realization of carbon reduction targets, the transformation in the field of energy production and consumption is the key to the transformation of China's energy structure. Changing the dominant position of coal in the traditional energy field and encouraging the development of clean energy can reduce the coupling between the transaction price of carbon emission reduction rights and the traditional energy price, and realize the clean transformation of energy production.

2) Developing green financial market.

Accelerating the construction of green financial market can help enterprises encourage enterprises to actively develop emission reduction technologies, optimize carbon asset accounting and management methods, and provide more financing opportunities for new energy enterprises to help them grow, which can more effectively promote the development of low-carbon technologies and achieve emission reduction targets.

3) Improve the trading mechanism of carbon emission rights.

At present, the development of domestic carbon market is still in its infancy. Since the formation of seven domestic carbon emission trading markets in 2013, the trading volume of CDM and CCER quotas has greatly increased and achieved good results, but it still faces some problems such as unreasonable initial allocation mechanism of carbon quotas, inaccurate carbon emission accounting of enterprises, and imperfect relevant laws and regulations. Further standardizing the domestic carbon emission trading system, optimizing the initial quota allocation method and strengthening the accurate accounting of carbon emissions of enterprises can achieve more efficient carbon emission management, improve carbon reduction efficiency and promote the realization of the "double carbon" goal.

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