Research on Forecasting Methods of Carbon Trading Price

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Abstract: The Global Carbon Market Progress 2019 released by International Carbon Action Partnership (ICAP) in March 2019 shows that since the launch of the EU carbon market in 2005, new systems have been established one after another and the share of global emissions covered by the carbon emissions trading system has doubled. With the steady advancement of carbon trading pilots in seven provinces and cities and the acceleration of national unified carbon market construction, China is about to usher in a comprehensive carbon-constrained era. The greenhouse gas emission rights represented by carbon dioxide have become a scarce commodity with financial value. Carbon emissions trading is also considered to be one of the most effective market economy instruments. Cost and price are the key indicators of carbon trading market. Research on carbon trading price will continue to stimulate technological innovation and market innovation of enterprises and inject new low-carbon power into economic growth.

1. Research Summary

How to ensure the formation of a relatively stable and reasonable price mechanism in the carbon trading market is the core issue of the development of the carbon trading market, and has always been the focus of academic research. At present, the domestic scholars' research on carbon trading price mainly focuses on the analysis of the influencing factors of carbon trading price and the research on the fluctuation law of carbon price. These studies provide a solid theoretical support for the mechanism design of Chinese carbon trading market and carbon emission control of enterprises. (1) Analysis of factors affecting carbon trading price. Scholars have analyzed the influence of multiple factors on carbon price. Hong Juan and Chen Jing (2009) set out from international demand factors, domestic supply factors, domestic government price limit factors, international prices and speculative factors to build a price function model for Chinese carbon trading market [1]. Chen Xiaohong and Wang Zhi Yun (2012) analyzed the supply, demand and market impacts and found that quota supply and energy price are the main influencing factors of transaction price [2]. Ma Huimin and Zhao Jingqiu (2016) analyzed the factors positively related to carbon price, such as traditional energy price, financial market prosperity and BEA transaction average price. The negative correlation factors are international CERs price, industrial development level and BEA transaction average price [3]. (2) Study on the fluctuation law of carbon price. Zhang Jie, Sun Lihong and Xing Zhencheng (2018) used ARCH model clusters to test the volatility characteristics of carbon emission trading prices based on the daily average trading closing prices of six pilot markets [4]. Zheng Zuting, Shen Fei and Lang Peng (2018) have shown that the BP artificial neural network model can be used to early warn the price fluctuation risk of carbon trading in Shenzhen [5].

Based on the above research, although many scholars take carbon price as the research object, few scholars predict carbon trading price. Although carbon price is a dynamic and unstable price time series, the prediction is difficult, but the research shows that carbon price can be predicted, but more short-term prediction, the accuracy of prediction depends on the treatment of carbon price and the technical methods used. Therefore, this paper uses grey prediction method and Markov model to predict carbon price respectively, in order to find an appropriate prediction method and provide valuable reference for the supervision of Chinese carbon trading market and the management of enterprise carbon assets.

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2. Grey Prediction Model

The grey system theory takes "small sample" and "poor information" uncertain systems with "part information known and part information unknown" as research objects. Therefore, the gray prediction method is suitable for price prediction with short time and small data volume, and has high precision, and is widely used for price prediction in many markets. In grey prediction, GM (1,1) model is the core and the most commonly used model. Therefore, this paper uses GM (1,1) model to predict carbon trading price.

2.1 Model building

GM (1,1) is a first-order differential equation model in the form of:

$$\frac{dx}{dt}+ax=u \tag{1}$$

Let's set a non-negative primitive sequence:

$$X^{(0)}=\{x^{(0)}(1),x^{(0)}(2),\ldots,x^{(0)}(n)\} \tag{2}$$

Make a cumulative addition to and get the generated sequence as:

$$X^{(1)}=\{x^{(1)}(1),x^{(1)}(2),\ldots,x^{(1)}(n)\} \tag{3}$$

Among them $x^{(1)}(k)=\sum_{i=0}^{k}x^{(0)}(i),k=1,2,...n$. So,The whitening differential equation of GM (1,1) of $x^{(0)}(k)$ is:

$$\frac{dx^{(1)}}{dt}+ax^{(1)}=u \tag{4}$$

Where a is the development gray number and u is the gray amount.

$$\text{Make } Y=\begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix},B=\begin{bmatrix} -\frac{1}{2}(x^{(1)}(1)+x^{(1)}(2)) & 1 \\ -\frac{1}{2}(x^{(1)}(2)+x^{(1)}(3)) & 1 \\ \vdots & \vdots \\ -\frac{1}{2}(x^{(1)}(n-1)+x^{(1)}(n)) & 1 \end{bmatrix} \tag{5}$$

The parameter vector $\hat{a}$ can be obtained by least squares method, ie

$$\hat{a}=(B^{T}B)^{-1}B^{T}Y \tag{6}$$

Then the solution of the whitening equation is:

$$\hat{x}^{(1)}(k+1)=[x^{(0)}(1)-\frac{u}{a}]e^{-ak}+\frac{u}{a}, \text{ k=0,1,… ,n} \tag{7}$$

Restore to original data

$$\hat{x}^{(0)}(k+1)=(1-e^{a})[x^{(0)}(1)-\frac{u}{a}]e^{-ak}, \text{ k=0,1,…,n} \tag{8}$$

2.2 Empirical analysis of the model

Beijing has implemented strict carbon allocation, with high reliability of the data, and has played a good pilot and demonstration role. Therefore, this paper selects the carbon trading data (May 16, 2019-June 13, 2019) published by the Beijing Electronic Trading Platform for Carbon Emission Rights to predict the carbon price. The results of predicting G(1,1) prediction using GSTAV7.0 software are as follows:

Table 1 G(1,1) prediction result

Serial number	Actual data	Simulated data	Residual	Relative simulation error
2	73.660	78.079	-4.419	5.999%
3	77.120	78.285	-1.165	1.511%
4	83.880	78.492	5.388	6.424%
5	82.050	78.699	3.351	4.085%
6	82.490	78.906	3.584	4.345%
7	82.410	79.114	3.296	3.999%
8	71.820	79.323	-7.503	10.447%
9	77.360	79.532	-2.172	2.808%
10	77.370	79.742	-2.372	3.066%
11	78.000	79.952	-1.952	2.503%
12	81.040	80.163	0.877	1.082%
13	81.090	80.375	0.715	0.882%
14	81.900	80.587	1.313	1.603%
15	81.860	80.799	1.061	1.296%

The calculated average simulation relative error is 3.575%.

The simulation results of the raw data and the simulated data are shown below.

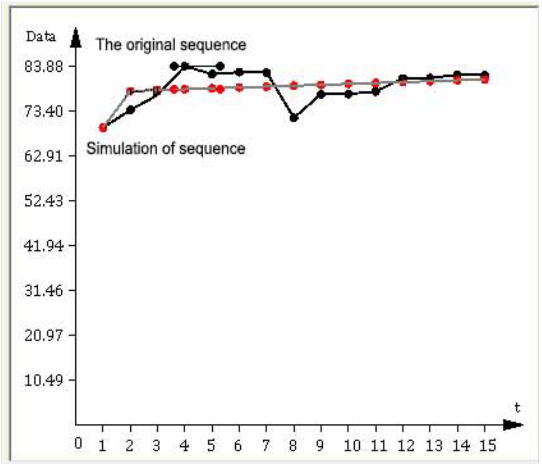

Figure 1 G(1,1) predicts simulation results

Table 2 Model precision judgment table

Accuracy level	Average relative error	Ratio of standard deviation
Class A	0.01	0.35
Second level	0.05	0.50
Level three	0.10	0.65
Level Four	0.20	0.80

According to the model accuracy judgment table in Table 2, 0.01<0.03575<0.05, the accuracy is two, we can further improve the prediction accuracy.

3. Markov Model Prediction

3.1 Markov model

Markov Chain is named after Professor Andrei A. Vezi Markov (1856-1922), and is still a hot research topic at home and abroad. The simplest type of Markov prediction method is to predict the most likely state in the next period:

The specific steps are:

Step 1: Divide the state of the predicted object. 1) The predicted object itself has obvious state boundaries; 2) It is not obvious, and it is comprehensively investigated and understood at the time of division, and analyzed in combination with the purpose of prediction.

Step 2: Calculate the initial probability. The state probability obtained by analyzing historical data according to actual problems becomes the initial probability.

Step 3: calculate the state transition probability and get the one-step transition probability matrix P_1;

The most basic is the one-step transition probability P(E$_i \to E_j$), which represents the probability that a certain time state E$_i$ transits to the next time state E_j through one step, and can be simply recorded as P$_{ij}$.

The matrix formed by the set of all the primary transition probabilities of the system is called the one-step transition probability matrix, which is simply called the state transition probability matrix.

$$P = \begin{bmatrix} p_{11} & p_{12} & p_{1j} & p_{1n} \\ p_{21} & p_{22} & p_{2j} & p_{2n} \\ p_{i1} & p_{i2} & p_{ij} & p_{in} \\ p_{n1} & p_{n2} & p_{nj} & p_{nn} \end{bmatrix} \quad 0 \le P_{ij} \le 1 \quad \sum_{j=1}^{n} P_{ij} = 1 \quad \text{(i,j=1,2,…n)} \tag{9}$$

Let P be the state transition probability matrix, then the k-step transfer matrix is:

$$P^{(k)} = P^{(k-1)} \times P \tag{10}$$

Step 4: Forecast according to the transition probability matrix:

$$X_{t+1} = P_1 X_t . \tag{11}$$

Where X_{t+1} represents the state of the $t+1$th and X_t represents the state of the tth day.

3.2 Empirical analysis of the Markov model.

(1) The prices are first classified. In order to facilitate the implementation of the program, the following classification methods are adopted:

a) finding the maximum value and the minimum value of the data sequence; max=83.88;min=71.82

b) Select the quarter point closest to the maximum and minimum values as the segment point of the segment; As follows:

Category 1:[71.5,74); Category 2: [74, 76.5); Category 3: [76.5, 79); Category 4: [79, 81.5); Category 5: [81.5, 84);

c) Since it is mainly for short-term forecasting, it is assumed in the classification that the predicted price will not break the upper limit or the lower limit, in this paper: 84 and 71.5.

(2) After classification, the transfer matrix is obtained:

$$F = \begin{bmatrix} 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 2 & 0 & 0 \\ 0 & 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 & 4 \end{bmatrix} \tag{12}$$

(3) Further obtaining a transfer frequency matrix:

$$P = \begin{bmatrix} 0 & 0 & 0 & 0 & 0.2 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0.5 & 0 & 0 \\ 0 & 0 & 0.25 & 0.5 & 0 \\ 0 & 0 & 0.25 & 0.5 & 0.8 \end{bmatrix} \tag{13}$$

(4) The prediction results obtained from model $X_{t+1} = PX_t$ are shown in Figure 2.

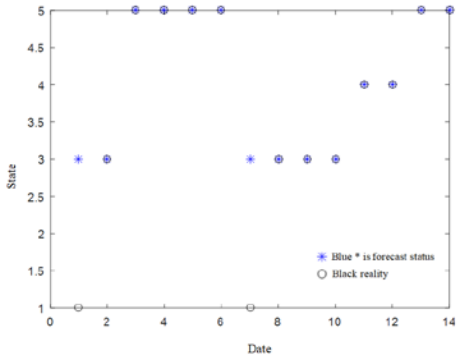

Figure 2 Markov prediction results

Thus, the predicted value, absolute residual value and residual graph of Markov model can be obtained. The residual plot is shown in Figure 3, and the predicted value and absolute residual value are shown in Table 3.

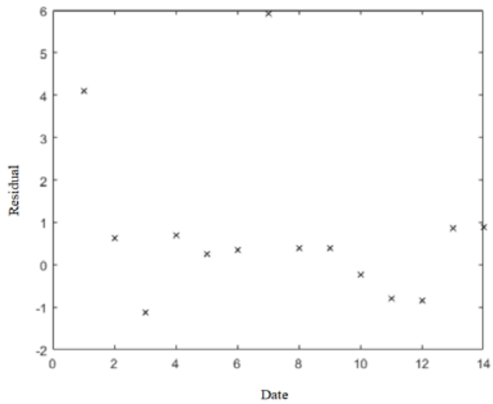

Figure 3 Markov prediction result residual graph.

Table 3 Absolute residual value of Markov model

	True value	Predicted value	Residual	Relative error
2019/5/17	73.66	77.75	4.09	0.055525
2019/5/20	77.12	77.75	0.63	0.008169
2019/5/21	83.88	82.75	-1.13	-0.01347
2019/5/22	82.05	82.75	0.7	0.008531
2019/5/24	82.49	82.75	0.26	0.003152
2019/5/30	82.41	82.75	0.34	0.004126
2019/6/3	71.82	77.75	5.93	0.082568
2019/6/4	77.36	77.75	0.39	0.005041
2019/6/5	77.37	77.75	0.38	0.004911
2019/6/6	78	77.75	-0.25	-0.00321
2019/6/10	81.04	80.25	-0.79	-0.00975
2019/6/11	81.09	80.25	-0.84	-0.01036
2019/6/12	81.9	82.75	0.85	0.010379
2019/6/13	81.86	82.75	0.89	0.010872

The calculated average simulation relative error is 1.117%, and the accuracy is level 1.

4. Comparison of Carbon Trading Price Models

By comparing the predicted values, residuals and relative errors of G (1,1) model prediction and Markov model prediction, it can be seen that (1) both G (1,1) model prediction and Markov model prediction have high accuracy for carbon price prediction in the future short-term trading day, and both can use short-term historical data to make high accuracy prediction for future trading day data. (2) compared with the G (1,1) model, the Markov model is more accurate and has more application value to the carbon activities of enterprises.

5. Conclusion

About 20% of global greenhouse gas emissions (11gtco2e, GT CO_2 equivalent) are covered by regional, national and sub national carbon pricing policies. As the result of market competition and the key factor to guide the allocation of carbon emission rights, carbon trading price is at the core of market mechanism. This paper takes the carbon trading price as the research object and forecasts the carbon trading price in order to provide theoretical value and empirical basis for the stability of the carbon market.

The accuracy of the prediction depends on the treatment of the carbon price and the technical methods used. In this paper, the grey prediction method and the Markov model are used to make short-term predictions on carbon price. The results show that the Markov model is more accurate than the G(1,1) model.

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