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Chaotic characteristic identification for carbon price and an multi-layer perceptron network prediction model

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ABSTRACT

Dec14 and Dec15, carbon prices of European Union Emissions Trading Scheme in phase III, are studied from the chaotic point of view. Firstly, chaotic characteristics of carbon price series are identified by three classic indicators: the maximum Lyapunov exponent, the correlation dimension and the Kolmogorov entropy. Both Dec14 and Dec15 have positive maximum Lyapunov exponents, and fractal correlation dimensions and non-zero Kolmogorov entropies, which demonstrates that the fluctuant nature of carbon price can be explained as a chaotic phenomenon. The carbon price dynamic system is recovered by reconstructing the phase space. Based on phase reconstruction, an multi-layer perceptron neural network prediction model is set up for carbon price to characterize its strong nonlinearity. The logic of the MLP are described in detail. K-fold cross-validation method is applied to show the validation of the model. Four measurements in level and directional prediction are used to evaluate the performance of the MLP model. Results show the good performance of the MLP network model in predicting carbon price.

1. Introduction

Carbon market is an important part of global emission reduction project. According to the requirement of Kyoto protocol about greenhouse gas, the European Union (EU) established the EU Emissions Trading Scheme (EU ETS) in January 2005. It is one of the earlier cap-and-trade systems restricting carbon dioxide emissions, which covers around 12,000 installations in 25 countries. Currently, the carbon futures market under EU ETS is the largest one in the world, whose transaction volume and price fluctuation both play a significant implication for the global carbon market (Kossoy & Guigon, 2012). Besides, carbon market presents unstable and fluctuant trends as influenced by the market mechanisms and some other factors such as climate agreement, weather variations and economic situation. Hence, it is an absolute necessity to make an accurate prediction for carbon prices so as to provide references for the other carbon markets.

Carbon prices analysis has caused great concern recently. Yu and Mallory (2014) pointed out that shock in the Euro/USD exchange rate has influence on the carbon credit market. Zhu, Ma, Chevallier, and Wei (2014) explored the dynamic behavior of European carbon futures price, indicting that carbon price behavior is asymmetric and the long-term bearish probability is greater than the long-term bullish probability. Daskalakis (2013) showed weak market efficiency of four carbon dioxide emission allowance futures in the phase II. Zhu and Wei (2013) made a prediction for the carbon price in phase II by comparing the predicting results of different models. Feng, Zou, and Wei (2011) analyzed the volatility of carbon futures price under EU ETS from a nonlinear dynamics point of view, proving that carbon market is weak and unstable despite having general market characteristics.

These studies above provide available reference for the analysis of carbon futures price. However, they mainly aimed at phase I and phase II and little researches involves the aspect of carbon prices predicting in phase III. As we all know, launched in 2005, the EU ETS is now in its third phase, running from 2013 to 2020. In order to strengthen the system, a major revision approved in 2009, which means the phase III is significantly different from phases I and II and far more harmonized than before based on rules. Besides, Chen, Wang, and Wu (2013) showed both price mechanism and volatility are dramatically different between phase I and phase II. Therefore, we wonder it is valuable to study the carbon prices in the new phase.

In recently years, various approaches have been developed for time series predicting, including linear and nonlinear approaches. The autoregressive integrated moving average (ARIMA) model was most widely adopted linear one. However, the ARIMA model has no effect on digging nonlinear characteristic hidden in a time

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series. More attention has been paid to nonlinear models, especially the artificial neural network (ANN) due to its excellent nonlinear modeling capability. Being capable of mapping any linear or non-linear functions, the ANN has been applied in various fields (Atsalakis & Valavanis, 2009; de Oliveira, Nobre, & Zarate, 2013; Firat & Gungor, 2009; Kolarik & Rudorfer, 1994; Shafie-khah, Moghaddam, & Sheikh-El-Eslami, 2011). Among the ANN models, the multi-layer perceptron (MLP) neuron network is the most widely used in time series predicting (de Oliveira et al., 2013). It depends on the network structure (topology,connections,neurons number) and their operational parameters (learning rate, momentum, etc), whose network architecture has a obvious effect on the results performance.

The main object of the paper is to identify the chaotic characteristics of the carbon prices in phase III and forecast the trend of the carbon price in a short time. We will adopt the maximum Lyapunov exponent, the correlation dimension and the Kolmogorov entropy to identify the chaotic characteristics. Then we will make a prediction for the carbon prices based on an MLP network prediction model.

The remainder of the paper is structured as follows. Section 2 describes the data source in the paper. Section 3 presents the chaotic characteristic analysis of carbon prices. Detailed logic of the MLP are described in Section 4. Section 5 shows the experimental test and results. The last section devotes to the overall conclusion.

2. Data source

We consider carbon futures prices of the EU allowance (EUA) from the European Climate Exchange (ECX). Locating in London, the ECX is the largest carbon market under the EU ETS, in which there are spot, futures, options of the EU allowance (EUA) and Certified Emission Reduction(CER) and the trading volume of EUA is the largest. Two series of carbon futures prices, Dec14 and Dec15, are selected as the experimental data, both coming from the EUA. For Dec14, limited to the website permission, the daily trading data from April 8, 2008 to March 31, 2014 are chosen, exclusive of public holidays, with a total of 1546 observations. Dec15 is from August 6, 2010 to March 31, 2014, exclusive of public holidays, with a total of 953 observations. The time series plots of Dec14 and Dec15 are presented in Fig. 1. We can see that carbon price presents high uncertainty and nonlinearity.

3. Chaotic characteristic analysis of carbon price series

We shall show that carbon prices of Dec14 and Dec15 are chaotic from aspects of the maximum Lyapunov exponent, the correlation dimension and the Kolmogorov entropy.

Let $x(t)$ be the carbon price at time $t, t = 1, \ldots, N$. Supposing the carbon time series $x(t)$ is generated by a dynamical system. Next we will judge whether this system is deterministic stochastic and linear or nonlinear. Chaotic time series analysis is a powerful method to fulfill this goal. By this theory, dynamic of the one-dimensional carbon price can be recovered in a higher-dimensional space.

For chaotic time series analysis, the crucial step is the reconstruction of state space, which generally is an m-dimension space. For the reconstruction of state space, we have various approaches to choose. But the time delay coordinate method is the best selection, as which can keep the dynamical properties of the original system (Parker, 1989). This method is to draw a time series on one axis while contrasting the same series on the other axes with a time delay.

Now we construct the phase space $\{Y(t)\}$. Based on the Takens' method (Takens, 1986), a point $Y(t)$ in the state space can be described by

$$Y(t) = [x(t), x(t-\tau), \ldots, x(t-(m-1)\tau)] \tag{1}$$

$t = 1, 2, \ldots, N_m$, where m and τ are both positive integers called embedding dimension and delay time, respectively and $N_m = N - (m-1)\tau$. Thus, mathematically, $Y(t) \in R^m$ is a vector or a point in the construction phase space. If the dynamical properties of $x(t)$ is recovered in R^m space, then it can be recovered in a space with higher dimension than m. Thus we just need the minimum embedding dimension. To reconstruct the phase space, we must determine the two parameters $m$and τ. There are several methods to determine the appropriate embedding dimension and delay time, such as the mutual information (Fraser & Swinney, 1986), the false neighbors (Kennel, Brown, & Abarbanel, 1992) and the Cao's method (Cao, 1997), etc. We shall apply the Cao's method to calculate the τ and t_w, where t_w is the time window. Then m can be determined followed according to the equation between the minimum dimension m and $\tau : t_w = (m-1)\tau$ (Kim, Eykholt, & Salas, 1999). For Dec14 and Dec15, m are calculated be 3 and 2, respectively. We reconstruct the 3-D phase spaces for each series (see Fig. 2).

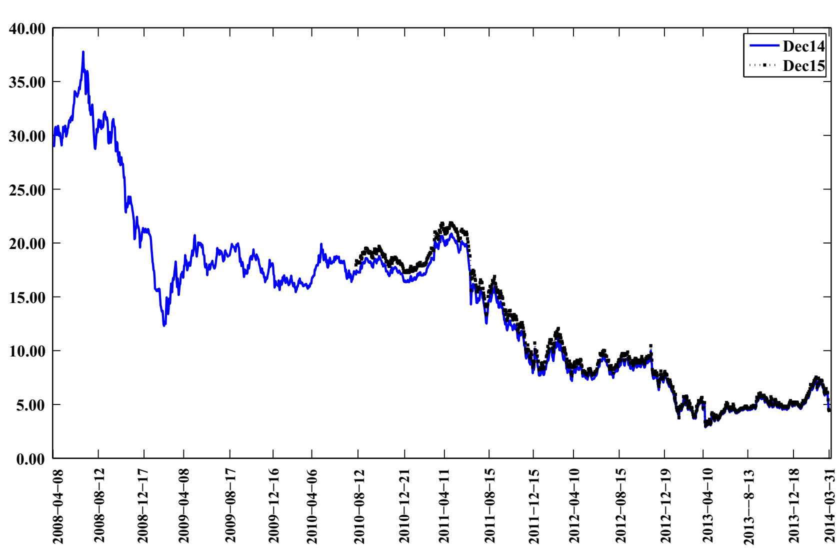

Fig. 1. Dec14 and Dec15 time series during April 2008–March 2014.