Journal of Multidisciplinary Engineering Science and Technology (JMEST)
ISSN: 2458-9403
Vol. 7 Issue 7, July - 2020

Exploring The Relationship Between Regional Carbon Markets Based On Complex Network Model

Qi Zhang, Xinghua Fan*, Qin Liu, Xiaohui Guo, Jiuli Yin
Faculty of Science
Jiangsu University, Jiangsu 212013
Zhenjiang, China
*Corresponding author: fan131@ujs.edu.cn

***Abstract*—The relationship between the pilot carbon markets is of great significance for macro-controlling the carbon market. This article selects the daily carbon trading prices of Beijing, Chongqing, Guangdong, Hubei, Shanghai, Shenzhen and Tianjin from June 19, 2013 to August 28, 2019 as sample data. Based on the coarse-grained method and sliding window algorithm, we constructed a price fluctuation network. By analyzing the undulating network and its topological characteristics in different regions, we obtain some valuable information. Analysis of network structure and node strength We found that the regions most similar to the simulated unified carbon market fluctuation behavior are Hubei and Shenzhen. The average path length indicates that the transfer period of the price fluctuation mode is shorter as 5-8 days. The results of the modular analysis show that the composition of enterprises involved in carbon trading in different regions is different. This study provides a way for market managers to better understand the laws of the market and also accumulates experience for the establishment of a national carbon market. Enterprises can reduce expenditures and increase returns by analyzing market fluctuations.**

Keywords—carbon market; complex network; regional relationship; price volatility

I. Introduction

The carbon emission trading market is a primary innovative practice of using markets mechanisms to control and reduce greenhouse gas emissions and promote green and low-carbon development. China took the initiative to assume the responsibility of great power. The carbon market is getting more and more attention. According to the United Nations and the world bank, the global carbon trading market had a capacity of 1.4 trillion yuan in 2012 and will reach 2.2 trillion yuan by 2020. In 2004, the European Union carbon market was established on the basis of the Kyoto protocol [1]. The EU carbon emission trading market is the largest carbon emission trading market in the world. In view of the effect of the EU emissions trading system in emission reduction, China started the operation of carbon emission trading in five pilot regions of cities and two provinces in June 2013 after the release of the guidance document on the pilot work of carbon emission trading. A national carbon trading market was established at the end of 2017, but is not yet operational. In the near future, China will become the world's largest carbon trading market.

Research on carbon markets has focused on three areas. First, some scholars focus on the prediction of carbon market prices. Zhu and Wei proposed a hybrid prediction model of carbon market based on least-squares support vector machine and particle swarm optimization algorithm [2], which has a significant effect on the prediction of eu carbon emission data. Yuansheng Huang. et al used machine learning method to predict the price of carbon trading market in China. The results show that the prediction model based on radial basis function (RBF) neural network has strong applicability [3]. Second, some scholars have studied the effectiveness of carbon markets. Zhao et al. analyzed the market efficiency of ETS pilot in China from four aspects: carbon price, trading volume, market liquidity and information transparency. The results show that although the system design of ETS has achieved initial success, the market efficiency of ETS pilot is not satisfactory [4]. They also put forward a number of policy proposals to improve market efficiency in China. Next, some scholars analyzed the factors influencing the carbon price. In order to explore the core problem of carbon price formation, Li and Lei et al. studied the influencing factors [5] of carbon market price. Through the analysis of multi-time series model and ARCH model, it is found that industrial income, energy price, government intervention and the number of participating companies will have a significant impact on the carbon price. Kaile Zhou and Yiwen Li studied the dynamic relationship between energy price, macroeconomic index, air quality and carbon emission trading price by using vector autoregressive-vector error correction model. The results show that there is a long-term equilibrium relationship between the carbon emission trading price and these indicators.

The fluctuation relationship of carbon market price in the pilot project is convenient for market managers and corporate shareholders to understand the market law. Wang and Gao [6] calculated the spillover effect of China's pilot carbon market and studied the structural characteristics and spatial correlation between carbon markets using social network analysis (SNA). Jia et al. [7] studied the transmission law of closing price fluctuation in five pilot cities: Beijing, Shanghai, Tianjin, Shenzhen and Guangdong. Jian Liu et al. [8] used a leveraged stochastic volatility (SV-L) model to characterize the price volatility characteristics of five pilot carbon markets in China. They found wide variations in the price of carbon in the five pilot markets. Among them, shenzhen, guangdong, Shanghai and Beijing have positive leverage effect, and hubei has anti-leverage effect.

Complex networks have been applied to many aspects of life such as life sciences [9], social sciences [10], economics [11], and finance [12]. In the network, we regard the research object as the node of the network and the relation between the nodes as the edge of the network. In recent years, some scholars have studied carbon market by network method. Jia et al. [7] studied the transmission law of price fluctuations in five carbon pilot cities based on complex network theory.

There are three motivations. First, China's carbon emission market is still in its early stage, and in-depth analysis of the carbon market price can accumulate experience for the market's further management. Second, the relationship between pilot carbon markets facilitates macro-control by market managers. Third, the traditional methods of analyzing price fluctuations cannot meet the needs of managers.

II. Methodology

A. Volatility mode

Convert price time series to price fluctuation symbol series taking the coarse-graining method. The price time series $\{X_t\}$ is the object of study. Let $\{X_t\} = \{X_1, X_2, \cdots, X_N\}$. The price fluctuation symbol is defined as the direction of daily returns. Letting $\Delta X_t = X_{t+1} - X_t$, the fluctuation symbol series is then written as

$$y_t = \begin{cases} N, & \Delta X_t < 0 \\ O, & \Delta X_t = 0 \\ P, & \Delta X_t > 0 \end{cases} \quad (1)$$

where the symbol 'P' means promoting, 'S' means stable and 'D' means decline, respectively.

Convert the sequence of price fluctuation symbols into a sequence of price volatility modes taking the sliding window algorithm. Setting the length of the sliding window is 5 and the sliding step size is 1. Then, a sliding Windows is defined as a price volatility modes such as 'PNOPN', 'PPPPP' and 'NNOOO'.

B. Volatility network model

We define a volatility network of price fluctuations. The elements in the volatility mode set are considered nodes. In the process of converting a wave symbol sequence into volatility modes, an edge is established between two modes with adjacent relations. Finally, we view the weight of an edge as the frequency of repeated occurrences of the edge from one mode to another.

C. Topological characteristics

Different price fluctuation modes have different importance, for which we calculated the topological characteristics of the network. The point weighted degree was defined as S_i [13], $S_i = \sum_{j \in H_i} w_{ij}$, where Hi represents the neighbor set of node i while w_{ij} epresents the weight of node i and j.

The average path length $< d_{ij} >$ is the average distance connecting any pair of nodes i and j, $< d_{ij} > = \frac{1}{N(N-1)} \sum_{i,j} d_{ij}$, where d_{ij} denotes the sum of the weights on the shortest path between the nodes i and j.

The average clustering coefficient $C^w(i)$ defined as follows [14]:

$$C^w(i) = \frac{1}{s_i(k_i - 1)} \sum_{j,t} \frac{(w_{ij} + w_{it})}{2} a_{ij} a_{jt} a_{ti}, \quad (2)$$

where k_i represents the number of edges associated with node i.

III. Data and Results

A. Data

This paper selects the daily carbon trading prices of seven cities (Beijing, Chongqing, Guangdong, Shanghai, Shenzhen and Tianjin) from June 19, 2013 to August 28, 2019 as samples. The dataset is achieved from the China Carbon Trading Network (http: //k.tanjiaoyi.com/). Considering that the market has 5 trading days per week, we use the method of sliding average to obtain the missing data. Generally, the daily price fluctuation sequence can reflect some characteristics of different pilot markets. However, from the perspective of macro-control, the sequence information obtained by the original analysis method cannot satisfy the market managers and enterprise stake-holders who are used to analyze the relationship between regional markets. Fig. 1 shows the trading prices and trading averages of the seven carbon markets.

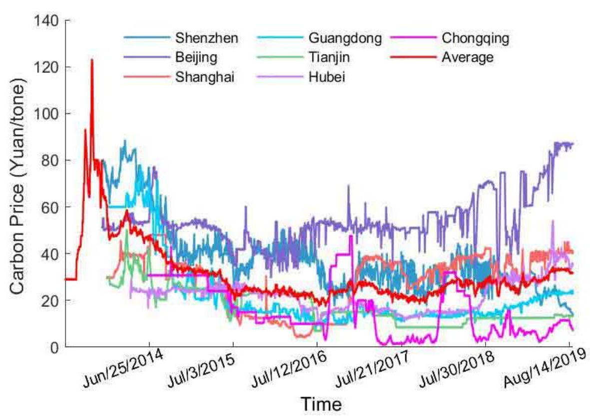


Fig. 1.Prices and average price for seven pilot carbon markets.

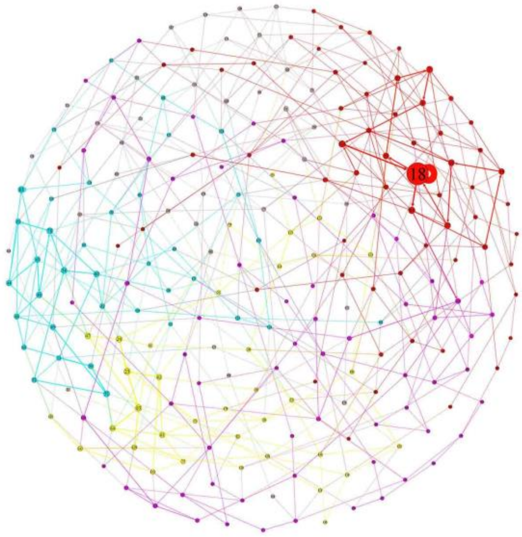
B. Network structure

In order to obtain more scientific and effective regional market relations, the author establishes price fluctuation networks. The price fluctuation mode is regarded as the node of the network. An directed edge is defined between adjacent modes generated in time order. The frequency of an edge between two modes is considered as an edge weight. Each mode represents the pattern of market volatility over time. Theoretically, there are 243 fluctuation patterns. In fact, different sets of patterns of carbon market fluctuations deviate from the theoretical values. We find that the price fluctuation pattern in Hubei province was 139 which set is the minimum among the seven pilot carbon markets. The Shanghai pilot carbon market is 235 which set is the maximum among the seven pilot carbon markets. Shenzhen carbon market was the established earliest one, while the price fluctuation patterns of shenzhen carbon pilot market is 176. This means that the length of market data volume does not have a linear growth relationship with the number of market volatility patterns. There are 116 volatility patterns about the seven pilot prices average. The volatility pattern of the average is lower than that of the seven pilots. This result indicates that different regions show differences in order to adapt to local development. Different regional settings of pilot carbon markets play different regional roles, which precisely reflects the rationality of the distribution of pilot markets.

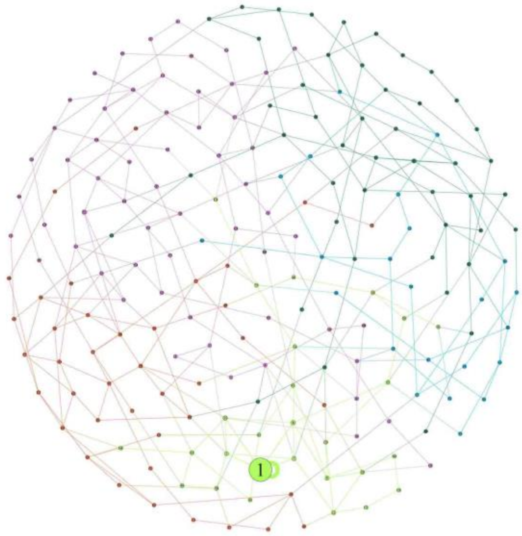
Fig. 2 shows networks of carbon price fluctuations in different pilots. The circles represent nodes, and the numbers in the circles serve as indices for the volatility modes. The size of the circle represents the weighted degree. Directed line segments between circles represent the edges of the network.

Different markets have different dominate volatility mode. In Fig. 2(a), 2(b), 2(c), 2(e) and 2(g), the largest nodes observed in each market are No. 18, No. 1, No. 2, No. 101, and No. 60.

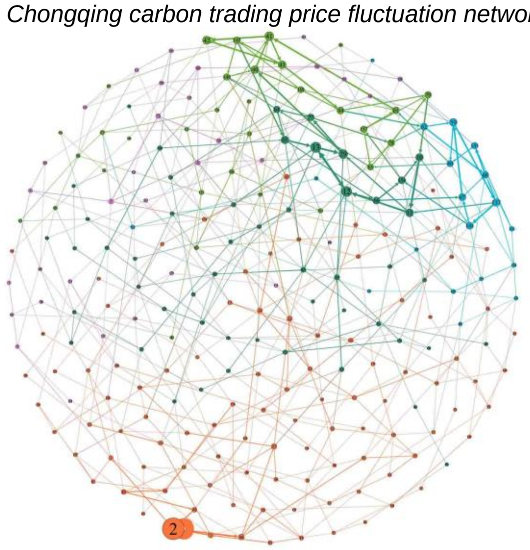
Through the one-to-one correspondence between node numbers and volatility modes, we find that the most important volatility modes in the history of the pilot carbon markets in Beijing, Chongqing, Guangdong, Shanghai, and Tianjin are 'SSSSS'. There is a positive correlation between market price changes and market activity. 'SSSSS' is a mode in which the transaction price is constant for a short period of time. This phenomenon indicates that five of the seven markets are less active. However, not all pilot markets are equally active. In Fig. 2(d), it is observed that the scales of nodes 6 and 31 are the largest. The corresponding volatility modes of nodes 6 and 31 are 'NPPNP 'and' PNPPN'. In Fig. 2(f), it is observed that the scale of node 59 is the largest. The corresponding volatility mode of node 59 is 'PNPNP'. Shenzhen is the earliest pilot carbon market in China. In a side view, the relatively high activity of the Shenzhen pilot carbon market reflects that the activity of the market may be affected by the initial stage of the market. Hubei is one of the later starting pilot markets. The rapid development of the pilot carbon market in Hubei is worth learning from other markets.



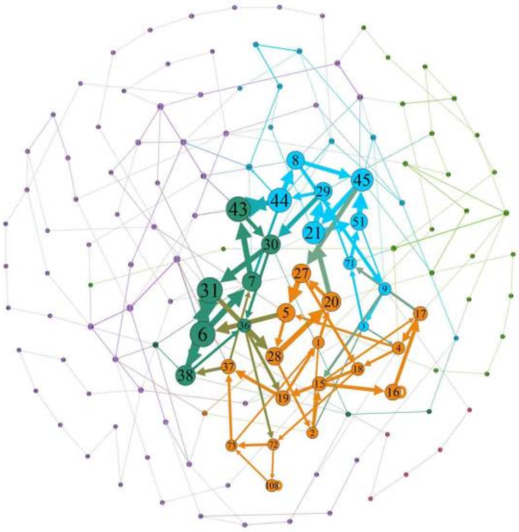
(a) Beijing carbon trading price fluctuation network.



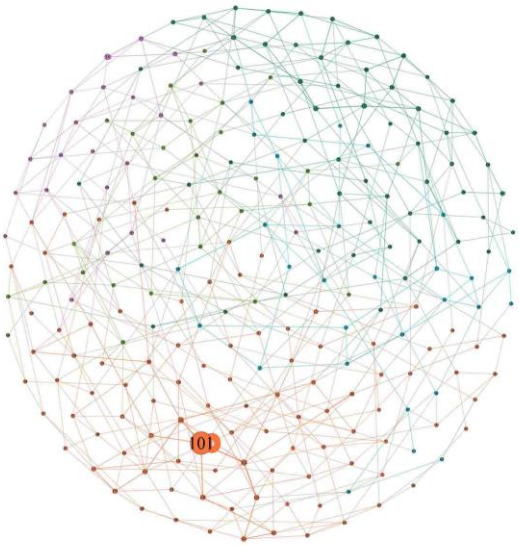
(b) Chongqing carbon trading price fluctuation network.



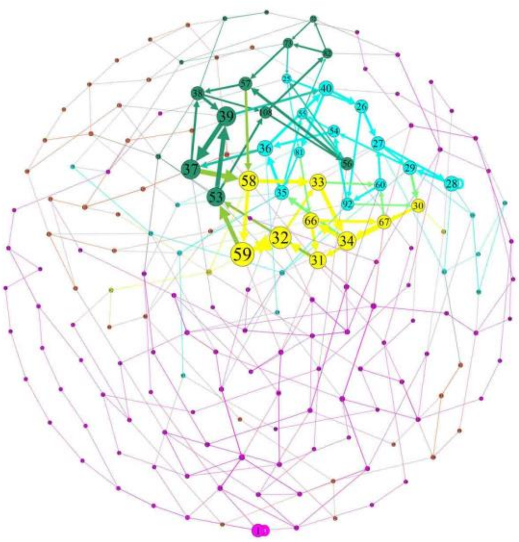
(c) Guangdong carbon trading price fluctuation network.



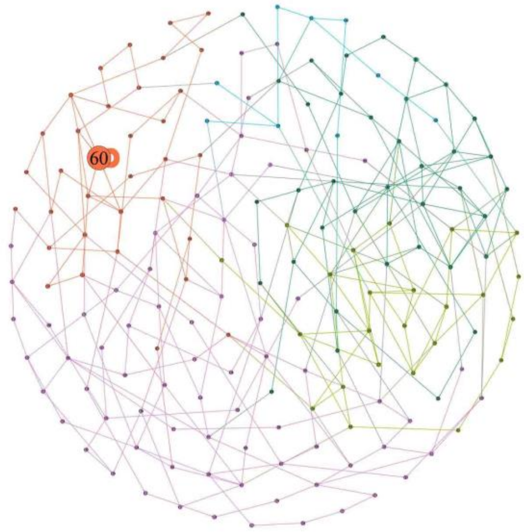
(d) Hubei carbon trading price fluctuation network.



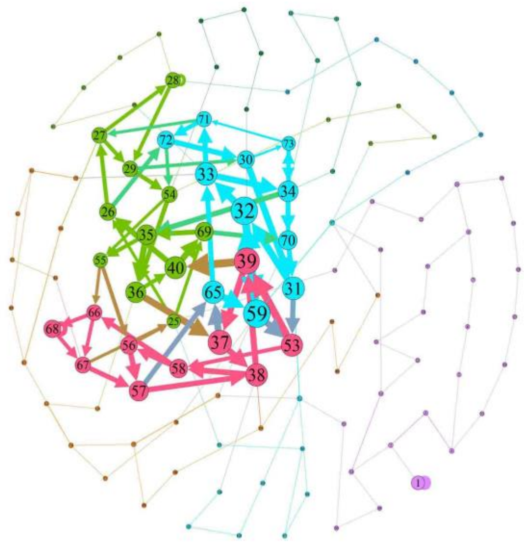
(e) Shanghai carbon trading price fluctuation network.



(f) Shenzhen carbon trading price fluctuation network.



(g) Tianjin carbon trading price fluctuation network.



(h) Carbon trading average price fluctuation network.

Fig. 2. Carbon trading price fluctuation network.

The network layout is different. Affected by the strongest nodes, the network layout of the pilot carbon markets in Beijing, Chongqing, Guangdong, Shanghai, and Tianjin presents a super-weak situation. In contrast, the network layout of Hubei and Shenzhen pilots is relatively complicated. The more complex the network layout, the smaller the difference in the importance of the volatility modes. Therefore, the stability of the carbon markets in Hubei and Shenzhen is relatively high.

Different carbon markets have different proportions of large and small companies. By modularizing the fluctuation modes of different pilot carbon markets, we find that the modularity indexes of seven pilot carbon markets all exceed 0.496. The number of pilot communities in Beijing, Chongqing, Guangdong, Hubei, Shanghai, Shenzhen and Tianjin is 5, 5, 5, 6, 5, 5 and 5, respectively. The nodes in the same community have the same color in Fig. 2. We find that the number of members varies from community to community. In addition, the importance of different nodes in the same community is also different. This result is closely related to the regional nature of the market.

The price fluctuations in the Chinese carbon market are most similar to Hubei and Shenzhen carbon markets. Nodes 32 and 59 have the highest strength in Fig. 2(h). Their corresponding volatility modes are 'PNPNP'and' NPNPN', respectively. We assume that the average price fluctuations of the seven pilot carbon market prices represent price fluctuations in the Chinese carbon market. For the seven important nodes and network structure of the carbon market, we find that the price activity of the Chinese carbon market is similar to the price activity of the pilot projects in Hubei and Shenzhen. Further analysis of the price fluctuation network can provide another basis for the similarity between the pilot and the national market.

C. Analysis of the topological characteristics

Topological characteristics can reflect the similarities and differences among regional markets from many aspects. We calculated the Average path length(APL),

Average clustering coefficient(ACC) and Average Weighted Degree(AWD) of the pilot markets in Table 1. The maximum value of the average clustering coefficient is only 0.014, which means that the clustering phenomenon is not significant. The weighted average of each pilot carbon market varies with the minimum value in Shanghai and the maximum in Hubei. Average path length ranges from 5.748 to 7.75 with the minimum value in Beijing and the maximum in Chongqing. This result shows that the needing time of the price fluctuation mode changing from one to another is from 5 days to 8 days to different pilot markets. The average path length in seven markets are all relatively small.

Fig. 3 shows the strength distribution of each carbon market. The strength distribution results for the seven markets are similar. The strength distribution of the nodes exhibits a long tail effect. It shows that the strength of most nodes is small, and only a few nodes strength are very big. Consistent with the smaller average path length in the table 1, it shows that the price fluctuation network has a small-world attribute. Therefore, we can find a small number of fluctuation modes is the main way of price fluctuations in each markets. Market managers can better manage the market only by understanding the market price changes. Corporate stakeholders can maximize returns through price fluctuations.

Table 1. Topological properties of eight price volatility networks.

	Beijing	Chongqing	Guangdong	Hubei	Shanghai	Shenzhen	Tianjin
ACC	0.012	0.011	0.007	0.013	0.011	0.013	0.014
APL	5.748	7.75	5.993	7.101	5.766	7.262	7.482
AWD	5.987	6.456	5.923	9.432	5.872	8.545	7.902

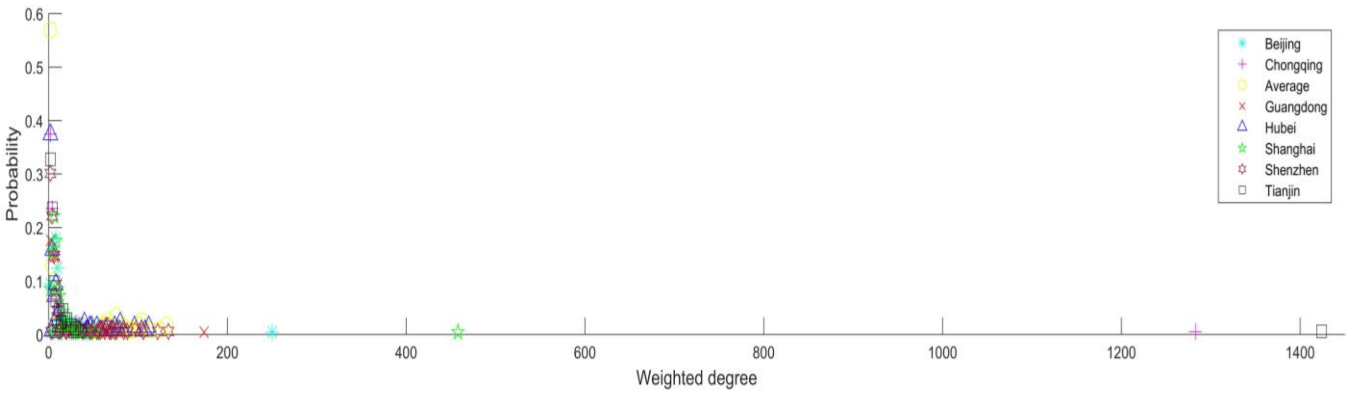


Fig. 3.Node strength distributions of different pilot carbon markets.

IV. CONCLUSION

In this paper, the carbon trading price sequence is converted into a price fluctuation symbol sequence by a coarse-grained method. Based on the sliding window algorithm, the price volatility symbol sequence is successfully mapped into a network form. The authors show a network of seven pilot carbon markets and mean simulation markets. Through the topological characteristics of complex networks, the relationship between the seven pilot carbon markets was analyzed in more depth. Based on this, the relationship between the seven pilot carbon markets and the average simulation market is also explored. We got some valuable results. First, there are different degrees of deviations between different sets of carbon market volatility patterns and theoretical values. Second, the importance of the same volatility ode is different in different markets. Third, from the perspective of price fluctuations, the Chinese carbon market is most similar to the pilot carbon markets in Hubei and Shenzhen. Fourth, the average path lengths of the seven pilot carbon markets and the average carbon market are relatively small and seem to have small-world characteristics.

The analysis of the relationship between the regional pilot carbon markets through complex network methods can provide some ways for the market to improve management and optimize business benefits. First, there is a certain inertia in the price fluctuation patterns of different pilot carbon markets over time. Market managers can better understand the laws of the market by analyzing common market fluctuations. Second, the probability that the same pilot carbon market will exhibit any one of the volatility patterns within a certain period of time is not exactly the same. When a company masters the market's price fluctuations, its shareholders can increase revenue. Third, the Chinese carbon market has not yet begun trading. Finding a pilot carbon market that is most similar to the development of the Chinese carbon market can provide valuable experience for the establishment and effective operation of the Chinese carbon market. Fourth, the cycle of the market's fluctuation mode is significant for the discovery of the market's laws. This is important for companies and market managers.

Although this article analyzes the similarities and differences between the markets, we choose a relatively small amount of indicators when comparing and analyzing the same indicators in each market. In the next stage, we will consider more indicators to analyze the differences and consistency of China's pilot carbon market from a wider scope. These laws may provide some basis for the operation of the national carbon market.

Acknowledgment

Research is supported by the National Natural Science Foundation of China (No. 71673116).

References

[1] E. Commission, A 'cap and trade' system, https://ec.europa.eu/clima/policies/ets, 2020.

[2] B. Zhu and Y. Wei, "Carbon price forecasting with a novel hybrid arima and least squares support vector machines methodology," Omega, vol. 3, 2013, pp.517-524, .

[3] Y. Huang, J. Hu, H. Liu and S. Liu, "Research on price forecasting method of china's carbon trading market based on pso-rbf algorithm," Systems Science & Control Engineering, vol. 2, 2019, pp.40-47.

[4] X. gang Zhao, G. wu Jiang, D. Nie and H. Chen, "How to improve the market efficiency of carbon trading: A perspective of china," Renewable and Sustainable Energy Reviews, 2016, pp.1229-1245.

[5] H. Li and M. Lei, "The influencing factors of china carbon price: a study based on carbon trading market in hubei province," Iop Conference, vol. 5, 2018, pp.052073.

[6] W. Qian and G. Cuiyun, "Research on the spillover effect of the pilot carbon trading markets in china: Based on sextuple var-garch-bekk model and social network analysis," Wuhan University Journal (Philosophy & Social Sciences) , vol. 6, 2016, pp. 57-67.

[7] J. Jia, H. Li, J. Zhou, M. Jiang and D. Dong, "Analysis of the transmis- sion characteristics of china's carbon market transaction price volatility from the perspective of a complex network," Environmental Science and Pollution Research, vol. 8, 2018, pp. 7369-7381.

[8] J. Liu, Y. Huang and C.P. Chang, "Leverage analysis of carbon market price fluctuation in china," Journal of Cleaner Production, vol. 245, 2020, pp.118557.

[9] M. Diykh and Y. Li, "Complex networks approach for EEG signal sleep stages classification," Expert Systems with Applications vol. 63 , 2016, pp.241-248.

[10] A. D. I. Kramer, J. E. Guillory and J. T. Hancock, "Experimental evidence of massive-scale emotional contagion through social networks," Proceedings of the National Academy of Sciences, vol. 24 , 2014, pp.8788-8790.

[11] W. Souma, Y. Fujiwara and H. Aoyama, "Complex networks and economics," Physica A: Statistical Mechanics and its Applications, 2003, pp. 396-401.

[12] J. L. Ticknor, "A Bayesian regularized artificial neural network for stock market forecasting," Expert Systems with Applications, vol. 14, 2013, pp.5501-5506.

[13] S. H. Yook, H. Jeong, A.-L. Barabási and Y. Tu, "Weighted evolving networks," 2001, pp.5835-5838.

[14] A. Barrat, M. Barthélemy, R. Pastor-Satorras and A. Vespignani, "The architecture of complex weighted networks," Proceedings of the National Academy of Sciences, vol. 11, 2004, pp.3747