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Network Performance Of Power Companies Based On China's Carbon Pilot

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***Abstract*—This paper explores the impact on the different carbon emissions trading pilots in China on power companies from the perspective of a complex network. We Used power companies from Chinas eight carbon emission pilot stock data to build a complex network of correlation coefficients. By analyzing the topological properties of network degree distribution, average path, and clustering coefficient. We found that the Guangdong carbon pilot power companies have a more important position than the Beijing, Hubei, and Shenzhen carbon pilot companies. Meanwhile, it provides useful enlightenment for decision-makers in designing carbon market mechanisms and investors in managing their investment portfolios.**

***Keywords*—power companies; complex network; Topological characteristics**

I. INTRODUCTION AND LITERATURE REVIEW

In order to alleviate the problem of global warming, countries around the world have adopted different methods. Among them, the carbon emission trading system is a relatively effective market mechanism[1]. Since the official launch of the EU emissions trading system in 2005, relevant research on the EU emissions trading system has become a hot topic. On the subject of EU carbon trading system, laws and infrastructure, a lot of research on the carbon trading market has provided good theoretical support for the current status and future development of the carbon trading market[2]. Subsequently, Canada, Japan, and other countries and regions also established their own carbon trading systems.In 2010, in the "Decision of the State Council on Accelerating the Cultivation and Development of Strategic Emerging Industries", the State Council clearly proposed to "establish and improve the major pollutants and carbon emissions trading system." The carbon emissions trading system has a practical basis and foundation in China. Subsequently, in 2011, the State Council and the National Development and Reform Commission successively issued documents agreeing to conduct pilot carbon emission trading in seven provinces (cities): Beijing, Tianjin, Shanghai, Chongqing, Hubei, Guangdong and Shenzhen. In 2015, China promised in the "China-U.S. First Joint Statement on Addressing Climate Change" and the Paris Climate Conference that China "plans to launch a national carbon emission trading system in 2017", which can be described as a highlight in the construction of my country's carbon market. Therefore, no matter from the experience of international carbon market construction or the practice of China's carbon market pilots, it is inevitable that China's power industry will be the first industry to be included in the carbon market, and almost all thermal power generation companies will be included. This paper uses a complex network method to establish a network of correlation coefficients for power companies in the carbon trading market, and studies the impact of different carbon emission trading pilots on power companies. This study has reference value and guiding significance for the design of carbon trading systems and the reduction of carbon emissions

Most of the literature focuses on the relationship between the carbon market and energy, and the data used are mainly based on electricity prices, studying the relationship between the electricity market and the carbon market. [3] to investigate the nonlinear structure and crosscorrelation between carbon and energy future markets across different time scales.[4] investigates information linkages and dynamic spillover effects between thecarbon and energy markets. [5] carbon emissions trading would also promote the clean production of electricity.The impact of the carbon market on the electricity market is weakening, and carbon prices need to be increased to enhance the vitality of the carbon market[6]. [7] analysis the correlation between daily carbon prices, electricity prices, and natural gas prices, it is found that the three have structural similarities. [8] studies the impact of carbon price on the EU electricity market, it is found that carbon price has a positive effect on the electricity market, but this positive effect is uneven.There are very few domestic documents to explore the relationship between the power financial market and the carbon market from the perspective of power company stocks. [9] indicated that changes in EU Emission Allowance (EUA) prices are critical to the performance of power companies' stocks, and found that changes in EUA carbon prices are positively correlated with the stock returns of important European power companies. Discover EUA The relationship with power companies is driven by market shocks. The volatility of power company stock returns is largely driven by the volatility of the EUA market[10]. [11] uses a network connection method to study the information spillover relationship between carbon price gains and power company stock returns. It shows that there is a strong information interdependence relationship between carbon price income and power stock income.

The stock linkage network

II. METHOD AND DATA

A. *The stock linkage network*

We construct a stock linkage network of electric power enterprises using the Pearson correlation coefficient of their stocks. Suppose there are N electric power enterprises in 8 Chinese carbon pilots and $X_i(t)$ are their closing stocks price at time t where $i=\{1,\cdots,N\}$. Let $B_i(t)=In(X_i(t+1)/X_i(t))$ be the logarithmic rate of return of stock i from period t to period $t+1$. Then we take those firms to be the node set $V=\{\mathrm{v}_1,\cdots,\mathrm{v}_\mathrm{N}\}$ of the complex network. Two nodes v_i and v_j are connected if their Pearson correlation coefficient C_{ij} of $B_i(t)$ and $B_j(t)$ is sufficient large. To be exact, the adjacent element a_{ij} is defined to be 1 if $C_{ij}>\theta_0$, where θ_0 is the threshold. The Pearson correlation coefficient C_{ij} is evaluated by

$$C_{\mathrm{ij}}=\frac{E(B_iB_j)-E(B_i)E(B_j)}{\sqrt{E(B_i^2)-E^2(B_j)}\sqrt{E(B_j^2)-E^2(B_j)}} \qquad (1)$$

Where $E(B_i)=\frac{1}{N}\sum_{t=1}^{N}B_i(t)$ is the average return of stock over the period N .

B. *Main features of complex networks*

- Node degree

The quantity of links connected to node vj in the network is known as the node degree k_{ij}. The degree of the node can be computed as

$$k_j=\sum_j a_{ij}\,. \qquad (2)$$

If nodes v_i and v_j are connected, then a_{ij} is equal to 1. Otherwise, a_{ij} is equal to 0. Usually, the node degree reflects the accessibility of the node and its importance in the network.

- Average path length

The distance dij between two nodes v_i and v_j is defined as the number of edges contained on the shortest path connecting them. The average path length L of the network is the mean of distances

$$L=\frac{\sum_{i\geq j}d_{ij}}{\frac{1}{2}N(N+1)}, \qquad (3)$$

where N is the total number of nodes in the network.

- The clustering coefficient

The clustering coefficient is used to describe the degree of aggregation of nodes in the network. The clustering coefficient of the node v_i is defined as

$$C_i=\frac{2E_i}{k_i(k_i-1)}, \qquad (4)$$

where E_i is the number of edges actually existing between the k_i neighboring nodes of node v_i. To measure how close the network is, the clustering coefficient C of the entire network is defined as the average of all the clustering coefficients of the nodes in the network:

$$C=\frac{1}{N}\sum_{i=1}^{N}C_i\,. \qquad (5)$$

The greater the clustering coefficient C, the more connections in the network.

- Betweenness centrality

The betweenness centrality of a node in the network depends on how much it participates in the information chain in the network. It is calculated as

$$B_m=\sum_{i\neq m\neq j}\frac{g_{ij}(m)}{g_{ij}}, \qquad (6)$$

where g_{ij} is the total number of shortest pathes from node v_i to node v_j, $g_{ij}(m)$ is the number of shortest pathes passing through[12].

C. Datas

The data for power companies stock, which were obtained from the Shanghai Stock Exchange andthe Shenzhen Stock Exchange. There are 73 power companies on the Chinese stock market, We screened out 32 power companies based on the list of control companies carbon pilot located in eight carbon pilot projects in Beijing, Shanghai, Guangdong, Tianjin, Shenzhen, Hubei, Chongqing, and Fujian. The stock data of power companies comes from the Big Wisdom Network. Due to the lack of data in 4 power companies,

28 power companies are selected as the research objects of this article. For missing data for each power company, we use the moving average algorithm to fill in the missing data. This paper studies the impact of carbon market before and after implementation on power companies, so the time is divided into 2010-2014, 2014-2017, 2017-2019. Then the data is substituted into (1) to obtain the connection relationship between power enterprises.

TABLE I. IDS,STOCK CODES AND FIRMS

ID	stock code	firm
1	601991	China Datang Corporation Ltd.
2	000027	ShenZhen Energy
3	000037	ShenZhen NanShan Power Co., Ltd.
4	000040	TUNGHSU AZURE
5	000531	GUANGZHOU HENGYUN ENTERPRISES HOLDING
6	000539	GUANGDONG ELECTRIC POWER DEVELOPMENT CO.,Ltd.
7	000591	Cecep Solar Energy Co.,Ltd.
8	000601	GUANGDONG SHAONENG GROUP CO., Ltd.
9	000690	GUANGDONG BAOLIHUA NEW ENERGY STOCK CO., Ltd.
10	000883	HUBEI ENERGY GROUP Co., Ltd
11	000939	Kaidi Eco Co., Ltd.
12	000996	GUODIAN CHANGYUAN ELECTRIC POWER Co., Ltd.
13	000993	MINDONG DIANLI
14	002256	Shenzhen Zhaoxin Energy Co., Ltd.
15	002249	Kelin Environmental Protection Equipment Co., Ltd.
16	600011	Huaneng Power International
17	600021	Shanghai electric power , lnc
18	600098	Guangzhou Development Group Incorporated
19	600116	Chongqing Three Gorges Water Conservancy and Electric Power Co.,Ltd.
20	600163	ZHONGMIN ENERGY Co., Ltd.
21	600027	Huadian Power International Co.,Ltd.
22	600452	Chongqing Fuling Electric Power Industrial Co.,Ltd.
23	600483	Fujian Funeng Co.,Ltd.
24	600578	Beijing Jingneng Power Co., ltd.
25	600795	GD POWER DEVELOPMENT CO., LTD.
26	600886	SDIC POWER HOLDING Co., ltd.
27	600868	Guangdong Meiyan Jixiang Hydropower Co.,Ltd.
28	600900	China Yangtze Power Co.,Ltd.

III. EXPERIMENTAL RESULTS

We determine the threshold by analyzing the topological structure of network constructed from different θ in a specific range. The range is decided by the relationship between the number of edges, average path length, cluster coefficient and threshold. Then the networks are built using the threshold.

We choose an appropriate threshold can better facilitate our research on the network. . If the threshold is selected too small, it will include too many edges of useless information, which will affect the research of the network topology; if the threshold is selected too large, too much information will be filtered out and the final judgment will be affected. Therefore, we need remove irrelevant edges to better observe the nature of the network. The threshold is determined according to the relationship between the threshold and the edge, average path, and clustering coefficient. Fig.1 shows the probability distribution of correlation coefficients between power companies. It can be seen that the correlation coefficients are mostly between 0.2-0.5. In

order to obtain a more accurate network threshold, we have analyzed the relationship between the threshold and the edge, the average path, and the clustering coefficient.

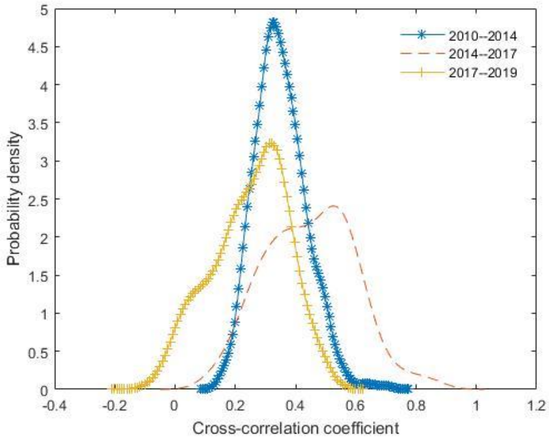
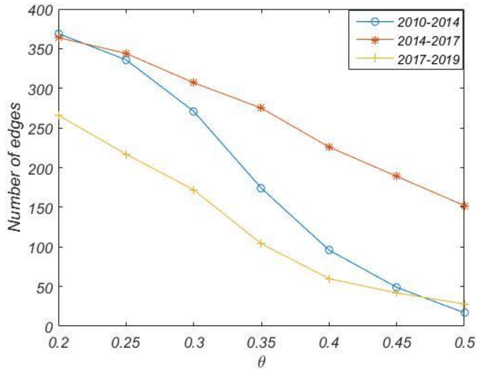
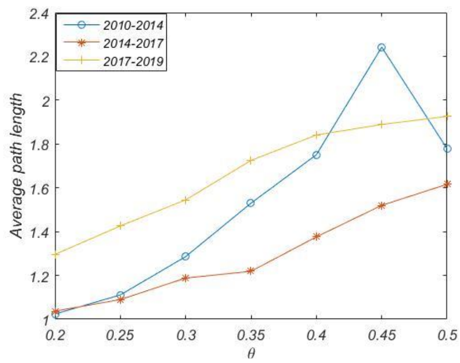


Fig. 1. *Probability Density Distribution of Correlation Coefficient of Electric Power Enterprise*

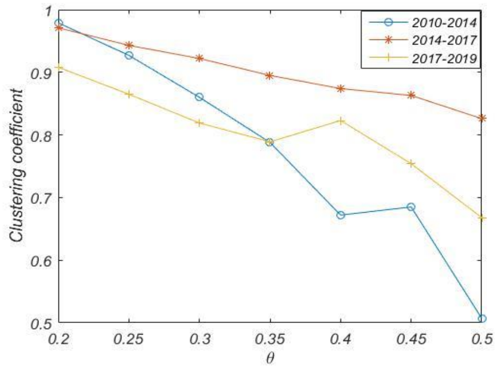
The determination of the power enterprise network threshold is shown Fig.2. Fig.2(a) represents the relationship between the threshold and the edge. Relationship, we found that the curve change between 0.2-0.3 is relatively stable, the change trend between 0.3-0.4 is relatively fast, and after 0.4, it is relatively stable. Fig.2(b) is the relationship between the threshold and the average path. The performance is similar to Fig.2(a), but the difference is that 0.4-0.5 shows irregular changes. Fig.2(c) is the relationship between the threshold and the clustering coefficient, the change trend of 0.2-0.3 is the same and stable, and after 0.3, it shows irregular changes. To sum up, we set a threshold network of power companies with a threshold of 0.3 to eliminate irrelevant edges .



(a) Network edges



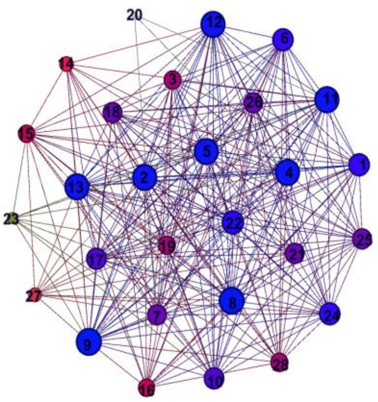
(b) Average path length



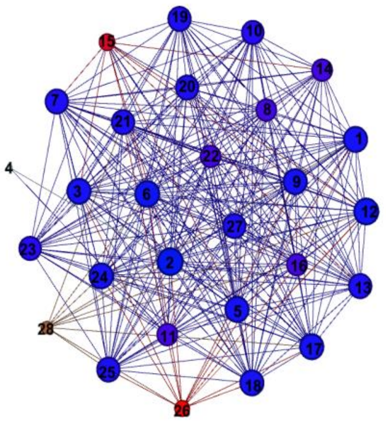
(c) Clustering coefficient

Fig. 2. *Network topology characteristics VS.threshold parameter*

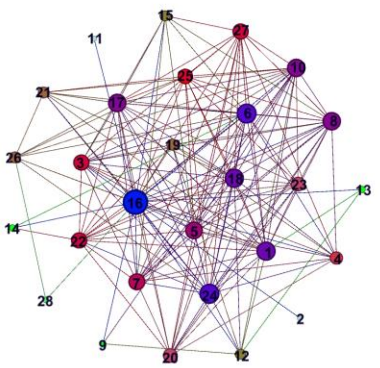
Fig.3 is the network diagram after setting the threshold, Fig.3(a), Fig.3(b) and Fig.3(c) are the network diagrams of power companies in different periods. The numbers on the nodes represent power companies Tab. 1. The size of the node represents the importance, and the location of the node represents the connectivity between the networks. The more in the middle, the stronger the connectivity. The connection between nodes means that the connection points are related, and the thickness of the connection represents the degree of correlation.



(a) 2010-2014



(b) 2014-2017



(c) 2017-2019

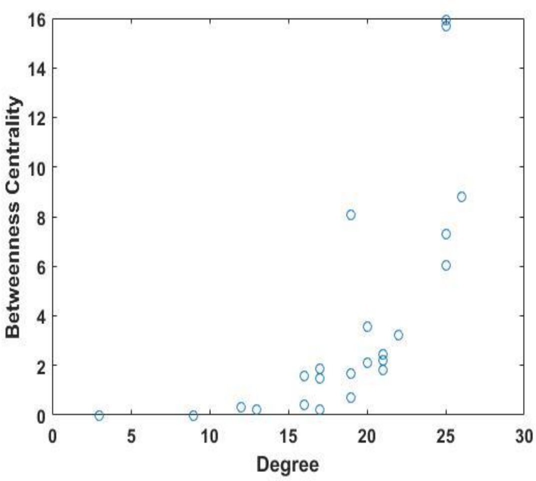
Fig. 3. *Topology graph of (a)(b)(c)power firms network with θ = 0:3 and (d)carbon price network with θ = 0*

Tab. 2 shows the rankings of the top 7 power companies in different time periods. We found that 11 companies are from Guangdong, 4 companies in Hubei and Beijing, and 2 companies are from Shenzhen. In 2010-2014, 2014-2017, and 2017-2019, there are 4, 4, and 3 power companies located in Guangdong, respectively. The power companies located in the Guangdong carbon emission pilot have an important position in the power company network, followed by Beijing the number of companies participating in carbon emission pilots has gradually increased, especially in 2017-2019, there were three relatively high-ranking power companies in Beijing's carbon emission pilots, implying that the more mature the carbon pilot system, the more important the power companies can be.

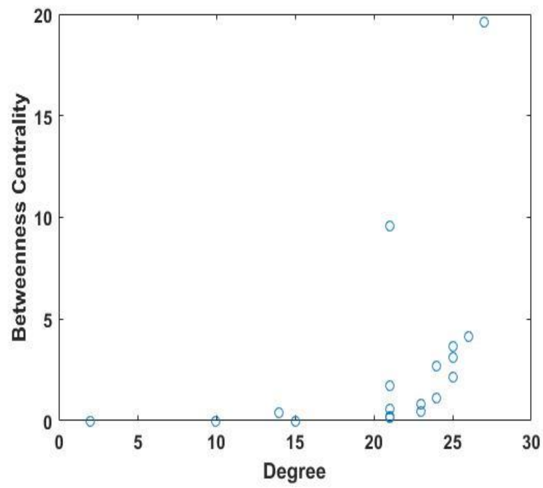
TABLE II. TOP 7 ELECTRIC POWER COMPANIES BY DEGREE

2010-2014			2014-2017			2017-2019		
ID	Degree	Carbon Emission Pliot	ID	Degree	Carbon Emission Pliot	ID	Degree	Carbon Emission Pliot
8	26	Guangdong	2	27	Shenzhen	16	27	Beijing
9	26	Guangdong	6	26	Guangdong	6	20	Guangdong
2	25	Shenzhen	12	26	Hubei	24	20	Beijing
4	25	Guangdong	1	25	Beijing	1	19	Beijing
5	25	Guangdong	3	25	Guangdong	18	19	Guangdong
11	25	Hubei	5	25	Guangdong	8	18	Guangdong
12	25	Hubei	9	25	Guangdong	10	18	Hubei

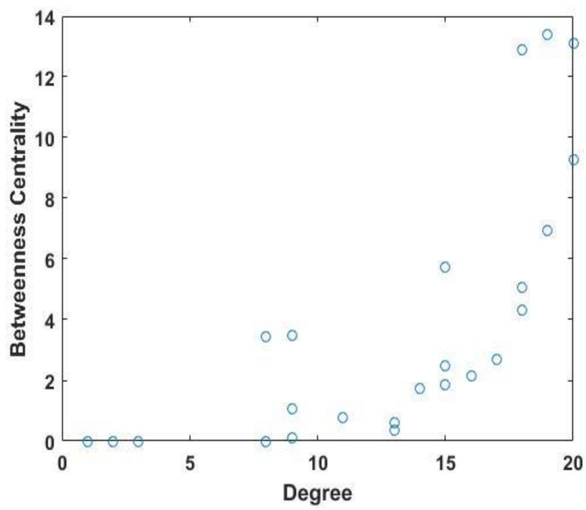
Fig.4 shows the relationship between the degree and the betweenness of power companies in different periods. Fig.4(a) shows the period 2010-2014. The betweenness and the degree are positively correlated, and the betweenness increases as the degree increases; Fig.4(b) is the 2014-2017 period, the relationship between the betweenness and the degree value is not obvious, but the overall can be found that the betweenness increases as the degree increases; Fig.4(c) is the relationship between the betweenness and the degree in 2017-2019 is more obvious than the normal relationship in 2014-2017. The higher degree and betweenness are concentrated in the upper right. Betweenness represents the transfer ability of the node. We found that the node with strong transfer ability also has a higher degree value in the network, indicating that stronger enterprises control the interdependence between enterprises. The relationship implies that companies with strong transmission capabilities will quickly pass on controlled companies if they have fluctuations.



(a) 2010-2014



(b) 2014-2017



(c) 2017-2019

Fig. 4. *Numbers besides circles represent the index of firms.*

IV. CONCLUSION

This article explores the impact of changes in the network structure of Chinas carbon pilot power industry by establishing a network diagram of the power industry correlation coefficients. Through network analysis, it is found that the importance of power companies in the Guangdong carbon pilot has gradually increased over time, followed by Beijing and Hubei The influence of power companies in the Shenzhen Carbon Pilot has also gradually increased.

We know that the maturity of the Guangdong carbon trading system ranks first among the seven carbon markets in China. All of its carbon trading pilots exercise strict regulatory management on the carbon market. The Shenzhen carbon trading market and the Beijing carbon trading market are at an intermediate level of maturity. [13] shows that the more perfect the carbon pilot system is, the more important the power industry is, and the power industry stock market can be controlled and invested by looking at the completeness of the pilot system. Conversely, observing the changes in the carbon pilot power industry network, we can find that changes in the companys stocks also have varying degrees of impact on the carbon pilot. Therefore, the changes in the power industrys stocks can also be used as indicators for the carbon pilot system.

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