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Visibility graph network analysis of natural gas price: The case of North American market

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HIGHLIGHTS

- The natural gas price visibility graph network is established.
- The natural gas price series is of long-range negative correlation fractal features.
- The network is of small-world and scale-free properties simultaneously.
- Impacts of the hubs and the underlying mechanisms are analyzed.

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ABSTRACT

Fluctuations in prices of natural gas significantly affect global economy. Therefore, the research on the characteristics of natural gas price fluctuations, turning points and its influencing cycle on the subsequent price series is of great significance. Global natural gas trade concentrates on three regional markets: the North American market, the European market and the Asia-Pacific market, with North America having the most developed natural gas financial market. In addition, perfect legal supervision and coordinated regulations make the North American market more open and more competitive. This paper focuses on the North American natural gas market specifically. The Henry Hub natural gas spot price time series is converted to a visibility graph network which provides a new direction for macro analysis of time series, and several indicators are investigated: degree and degree distribution, the average shortest path length and community structure. The internal mechanisms underlying price fluctuations are explored through the indicators. The results show that the natural gas prices visibility graph network (NGP-VGN) is of small-world and scale-free properties simultaneously. After random rearrangement of original price time series, the degree distribution of network becomes exponential distribution, different from the original ones. This means that, the original price time series is of long-range negative correlation fractal characteristic. In addition, nodes with large degree correspond to significant geopolitical or economic events. Communities correspond to time cycles in visibility graph network. The cycles of time series and the impact scope of hubs can be found by community structure partition.

1. Introduction

The development of low-carbon energy has significantly caught up in most countries helping to cope with global warming and ensuring energy security. Natural gas, is considered as the bridge to a low carbon future and its price volatility has

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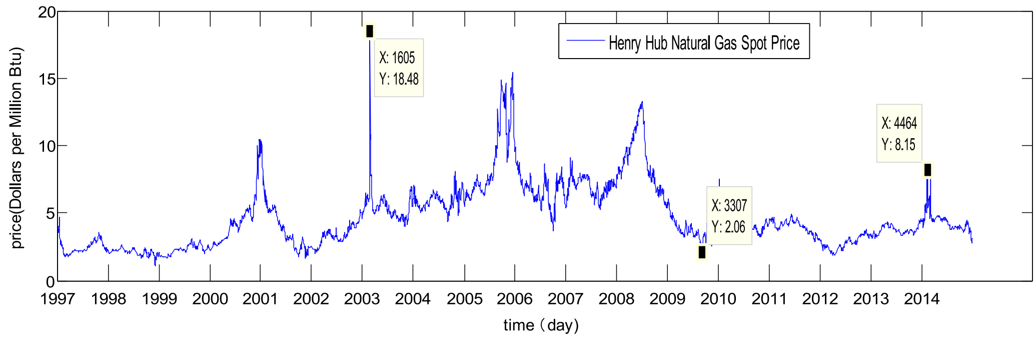


Fig. 1. Henry Hub natural gas spot price.

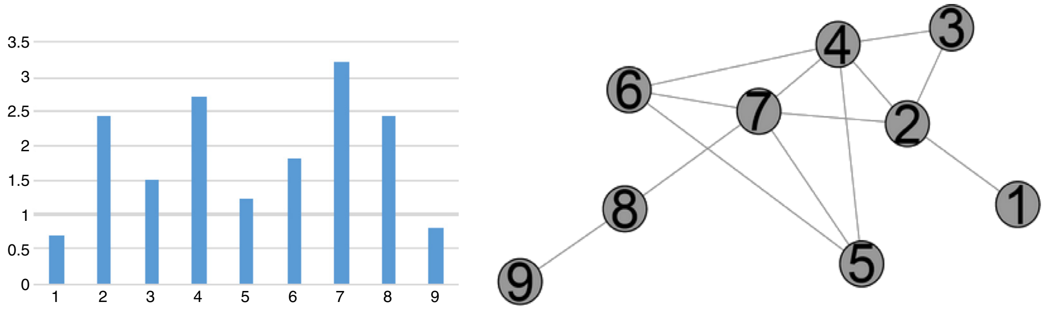
great influence on global economy. Natural gas reserves are abundant and its exploration is also promising. In 2014, the world's proven natural gas reserves were about 187.1 trillion cubic meters with reserve-production ratio of 54.1%.[1] The International Energy Agency (IEA)[2] believe that natural gas will continue to increase its share in global energy, with an annual growth rate of 2.4% until 2018. In another words, the world is entering a golden age of natural gas. Currently, due to the morphological characteristics of natural gas, a unified global natural gas spot market does not exist. According to different price standard, global market is mainly divided into three major regional markets: the North American market, the European market and the Asia-Pacific market. The North American market has gradually become the most mature market of them. It has a competitive market system and its market risk can be controlled by cash and derivatives. Therefore, research on the North American gas market is more representative. The natural gas spot price is a part of the natural gas market, and the North American natural gas spot price always fluctuating immensely. In Fig. 1, the prices have been fluctuating between \$1.7 and \$3.5/MMBTU before 2000. From 2000 to 2010, the extent of short-term changes in price is significant, considering the peaks and valleys. The highest price is \$18.48/MMBTU and the lowest is \$2.06/MMBTU. These prices from 2010 generally stayed below \$5/MMBTU. The high volatility of natural gas prices means that energy producers and distributors are often faced with high volatility risk. Therefore, in order to avoid market risks and improve energy security, it is of great importance to study the characteristics of price fluctuations of the North American natural gas market, which is exemplary to Europe and Asia markets.

Researchers at home and abroad have studied many kinds of price time series, like finance, energy, commodities, etc. For example, Shahmoradi in the process of data generation, studied the heteroscedasticity of natural gas futures prices, using ARCH and GARCH models to analyze time varying returns and volatility of Henry Hub natural gas futures contract market in the New York Mercantile Exchange (NYMEX) [1]. Orlowski investigated the dynamic evolution of price volatility and trading volume of the 10-year US Treasury note futures within the context of transition from pit to electronic trading. The empirical results showed that negative correlation exists between trading volume and price fluctuations, and the shift to electronic trading drives a substantial increase in trading volume, but not in price volatility of Treasury futures [2]. Chen studied the properties of 21 kinds of metal prices in 1900–2007, and found that the effect of the same kind of metal on metal price is much higher than the volatility spillover effect between all kinds of metal, and most of the fluctuations are caused by commodity specific risk rather than macroeconomic factors. Therefore, metal exporters can diversify metal exports to reduce the impact of metal price fluctuations [3]. Kanamura used the SDV model to analyze the volatility of natural gas prices in the US. It is found that there is reverse leverage effect and volatility equilibrium effect in the US natural gas market [4]. Auer tested daily effect in returns and volatility of crude oil using the virtual augmented GARCH model and found that: (1) Volatility on Mondays are much higher than all other weekdays. (2) Returns on Mondays tend to be lower than other weekdays. (3) Results are fairly robust to the choice of other frequently used GARCH model variants, like GARCH-M, TGARCH and CGARCH [5]. Goor analyzed the impact of supply and demand fundamentals to price fluctuations on the British gas market. It was observed that, many types of supply curves and linear supply curve lead to leverage effect through the GARCH-M and EGARCH model. At the same time, they found seasonal fluctuation effect is no longer significant in 2014, which is owing to the wider use of natural gas in power plants and higher liquidity of natural gas spot market [6].

Existing research works on natural gas price fluctuations often use statistical and econometric models to do quantitative analysis. With the development of complex network theory in various subjects, such as cellular networks, protein function networks, neural networks, etc., it has become a new approach to the study of energy. For example, An has studied the relationship between general trading countries through the establishment of a global crude oil trade network model. He found that, the international crude oil trade network is evolving into a stable, orderly and integrated system, and different types of events have different impacts on the import and export countries [7]. This paper adopted a new method—visibility graph algorithm which converts time series to complex network. We built the overall and five local visibility networks of

[1] The data comes from BP Statistical Review of World Energy 2015.

[2] The IEA (International Energy Agency) is an autonomous organization which works to ensure reliable, affordable and clean energy for its 29 member countries and beyond. The IEA has four main areas of focus: energy security, economic development, environmental awareness and engagement worldwide.



(a) A sample of time series.

(b) The corresponding visibility graph.

Fig. 2. Time series and the corresponding visibility graph network.

North American natural gas spot market. We analyze the price fluctuations by observing evolution characteristics of the corresponding network. The visibility graph method was first proposed by Lucas [8]. It was later applied to the study of the gold price [9], exchange rate [10], the financial price [11], the economic time series [12,13], and provides a basis for our research.

The main contributions of this paper are: (1) It provides a new method to study the spot price fluctuations of natural gas in North America, which also can be related to energy prices, such as coal, oil, solar, etc. (2) Combined with the degree distribution characteristics of NGP-VGN, selecting appropriate window size, the overall natural gas price series is divided into five 6-year time windows, which makes the research more detailed and targeted; (3) Degree and degree distribution, small-world characteristics and community structure of the network are investigated to analyze the characteristics of the fluctuation of natural gas price in and between each window.

The ensuing sections are structured as follows: Section 2 introduces the main theories and methods we used to establish the NGP-VGN. Section 3 outlines the data selection and the empirical analysis. Section 4 includes the main conclusions and policy recommendations.

2. Methodology

2.1. Visibility graph

Visibility graph [8], a bridge between time series and complex network, which can be used to investigate the overall and local features of time series through complex network theory. Every observation in univariate time series $\{x_i | i = 1, 2, \ldots, N\}$ can be converted into a node in network diagram. x_i is the observation of time i, we can say node i and node j are visible to each other, if

$$x_k \le x_i + \frac{x_j - x_i}{j - i}(k - i), \quad i < \forall k < j. \tag{1}$$

Connecting any two data which are visible, forms a visibility graph network where each node represents one observation of time series. Fig. 2 shows a sample of time series, and the corresponding visibility graph network. Characteristics of the original time series can be found from the corresponding visibility graph. Ordered (periodic) series converts into regular graphs, random series converts into exponential random graphs and fractal series into scale-free graphs [8]. In addition the temporal characteristics and the internal evolution mechanisms of time series can also be explained by the visibility graph algorithm.

2.2. Indicator system of visibility graph network

In this paper, three indicators of the North American NGP-VGN are studied: degree and degree distribution, the average shortest path length and community structure.

2.2.1. Degree and degree distribution

The degree of a node is defined as the number of other nodes it is connected to. It is called power-law distribution or scale-free distribution when degree distribution of the network can be expressed as $P(k) = ck^{-\gamma}$, and γ is the power-law index. Such networks have most nodes with low degree and a small amount of nodes with large degree. This is known as a heterogeneous network. Nodes with relative large degree are called "hubs" in the network. The importance of nodes can be measured by the size of their corresponding degree in the North American NGP-VGN. The greater the degree, the higher the impact of the node on price series.

2.2.2. The average shortest path length

The shortest path between node *i* and *j* in a network is a path whose number of edges connecting to the two nodes is the least, the distance d_{ij} between node *i* and node *j* is defined as the least number of edges between the node *i* and node *j*. The average shortest path length *L* is defined as the average distance between any two nodes, namely

$$L = \frac{1}{\frac{1}{2}N(N-1)} \sum_{i \geq j} d_{ij} \tag{2}$$

where *N* is the number of nodes in a network. The average shortest path length is known as the critical path length of the network. The mechanism of price fluctuations can be found through the average shortest path length in the North American NGP-VGN, and *L* represents the relevance of natural gas price fluctuations.

2.2.3. Community structure

Community structure is an important tool of meso-structure analysis of network. The association between nodes in one community is dense, and the connection between nodes divided in different communities is relatively sparse. This reason is that, nodes in one community have equal or similar properties. Some hidden rules can be found through the analysis of community structure.

There are many methods to detect community structure. We used the algorithm proposed by Blondel et al. [14]. This algorithm has high accuracy and fast running speed. It is derived from two iterations. First, each node in the network is regarded as a separated community. We then take any node *i* and find node *j*, a neighbor of node *i*, which makes the added value of modularity largest and positive. They are then merged into a new community, otherwise the node *i* stays in the original community. Repeat the same operation to all nodes until they reach the optimal division of community structure. At this point, the first phase ends. The second phase takes the communities from the first phase as nodes, the edge weight between two new nodes is equal to the edge weight between their original communities, and new community structure is obtained according to the algorithm in the first phase. The two phases are repeated until they reach a maximum modularity and the result is fixed. Modularity Q is calculated by

$$Q = \frac{1}{2w} \sum_{i} \sum_{j} \left(w_{ij} - \frac{w_i w_j}{2w} \right) \delta(C_i, C_j) \tag{3}$$

where w_i and w_j represent the intensity of node *i* and node *j* respectively, and $2w = \sum_i \sum_j w_{ij}$.

In the NGP-VGN, the number of communities reflects the cycle of natural gas price fluctuations. The connection of price fluctuations in the same cycle is stronger, whereas the relationship between different cycles is weak.

3. Empirical analysis

3.1. Data sources

The data analyzed is from Henry Hub natural gas spot price considering the period January 1, 1997–December 31, 2014 by EIA,[3] due to the limitation of data. And, the method used in this paper is to reveal the overall characteristics of natural gas price fluctuations, tiny change on study period will not affect the whole fluctuation mechanisms. The price is in US dollars per million British thermal unit. Missing data were estimated using the average values of two days before and after. According to the historical data of natural gas spot price, we established North American NGP-VGN. The characteristics of phases and the internal mechanisms of the natural gas price fluctuations can be shown by complex network theory.

3.2. Topological properties of the NGP-VGN

For a comprehensive analysis of the characteristics of natural gas spot price time series, we established the overall (1997.1.1–2014.12.31) and five local NGP-VGNs respectively. The size of windows may affect the nature of corresponding networks. Five 6-year windows of the time series are established and the first window is from January 1, 1997 to December 31, 2002. Each window moves three years to generate the next window, therefore, the two adjacent windows have three years overlaps. The reason for moving at three-year interval is to ensure that information from one 3-year overlap can be passed to the adjacent 3-year overlap in succession and this we think is very convenient and reliable. Each window has around 1565 nodes to build local visibility graph network. We study the evolution of some indexes of the NGP-VGN using complex network theory. The internal mechanisms of natural gas spot price fluctuations can be found by the comparative analysis of the overall and local visibility networks.

[3] EIA (The US Energy Information Administration) provides a wide range of information and data products covering energy production, stocks, demand, imports, exports, and prices; and prepares analyses and special reports on topics of current interest.

Table 1
The exponent of power law degree distribution of NGP-VGNs.

Time windows	1997–2014	1997–2002	2000–2005	2003–2008	2006–2011	2009–2014
γ	1.79	1.76	1.71	1.8	1.84	1.81

3.2.1. Analysis of degree sequence

According to the method defined in Section 2.2.1, we study the degree sequences of the overall and five local NGP-VGNs. In Fig. 3, natural gas spot price is in blue line, and the corresponding degree of every node is in green. Firstly, we can see that the degree observations of most nodes in the overall and the local window visibility graph networks are equal or have similar differences. This means that, the impact span of most natural gas prices does not exceed six years. It is therefore suitable to create 6-year window for the analysis of natural gas spot price time series. However, the node February 25, 2003 is exceptional. It has observation of degree 446 in the overall network and 346 in the local 2000–2005 window. In fact, this node corresponds to the outbreak of the Iraq war in 2003 which caused a shock to natural gas price with large ranges. Secondly, we find that high prices generally correspond to large degrees, but there are also exceptions. For example, spot prices stay high from September 23, 2005 to the end of 2005, but their corresponding degrees are very small. There was hurricane Katrina on August 25, 2005 which made landfall in Florida causing a sharp decline of gas production. Gas price continued to rise, and reached a high value of \$14.84/MMBTU on September 22, 2005, with its degree rising to 143. Then the price soared to \$15.39 on December 13, 2005, but the corresponding degree was only 19. We arrived at the conclusion that, nodes with large degree are not simple local maximum or overall maximum, but have great influence on neighboring nodes. After hurricane Katrina, the degree of natural gas price has experienced a growth, then achieved maximum on September 22, 2005. Since then the degree sequence stays very small. It can be interpreted that, the high prices after September 22, 2005 are as a result of the hurricane, but the price fluctuations themselves did not have great influence. Thirdly, the mean and variance of degrees (in parentheses under each window's plot, mean is the former, variance is the latter) are both big on the overall visibility network. This is due to the degree of unusual nodes with high price is large, and the degree of frequent nodes with low price is small. A small amount of large-degree nodes and a great number of low-degree nodes led to a great variance of degrees. Windows 1997–2002 and 2000–2005 have similar situation with the overall network. In relation to the overall network, the mean and variance of degrees of the remaining three windows are small. This may be due to price fluctuations in these windows which are of similar amplitudes or high frequency. It can also be attributed to a few important events which have huge influence on price fluctuations occurred in these windows. These fluctuations may be mostly affected by short-term changes of demand and supply, or seasonal factors.

3.2.2. The degree distribution of the NGP-VGN

In this section, we first analyze the degree distribution of the overall NGP-VGN (1997.1.1–2014.12.31). Fig. 4 shows that, in the double logarithmic coordinate axis, the overall NGP-VGN has a power-law degree distribution, and γ represents the exponent of power-law degree distribution which is 1.79. This indicates that, the North American NGP-VGN is a scale-free network. Only a few of nodes have large degrees, whereas the degrees of majority nodes are very low, which partly reflects the volatility of the original time series. In a certain range, nodes with high visibility are greatly affected by previous price fluctuations or have great influence on subsequent price fluctuations.

Then, in order to compare with the results above, we investigate degree distribution of the random rearranged natural gas price series, and find that it is similar to the exponential distribution, as shown in Fig. 5. According to Lucas et al., random series converts into exponential random graphs and fractal series into scale-free graphs [8]. Therefore the overall natural gas price series is a fractal time series. Fractal time series has two fractal features: one is scale-invariance, that is, time series under different time scales, i.e., month, week, day, and so on having similarity in their statistics. The other is self-similarity, that is, certain similarities may exist between any local and the whole series. In natural gas price visibility network, it means that natural gas price fluctuations in the future are likely to be similar to a certain period in the past. Meanwhile, we calculated the Hurst's exponent H of the time series by the rescaled range analysis (R/S) method, and the result was $H = 0.4607$. Hurst's exponent has the following characteristics: (1) $0 < H < 0.5$, long-range anti-persistence; (2) $0.5 < H < 1$, long-range persistence; (3) $H = 0.5$, without long-range persistence [15]. This shows that the North American natural gas price time series is of long-range anti-persistence. There is no strong state persistence, that is, in time series it is possible to have an up–down or down–up occurrence in a short time interval. It also has tendency of mean reversion, and reversal of price fluctuations will be repeated frequently. The North American natural gas price series is made of frequent reversals, which indicates that, the series is in a state of agitation, that is, there is no sustained upward or downward trend.

Finally, we calculated the exponent of power-law degree distribution of local visibility graph networks in Table 1 having range of the values from 1.71 to 1.84. Therefore, all these local series are fractal time series. The power-law indexes of the last three windows are larger than that of overall network, which is 1.79 as shown in Fig. 4. It illustrates that the probability of nodes with large degree decreases and nodes with low degree increases in last three windows.

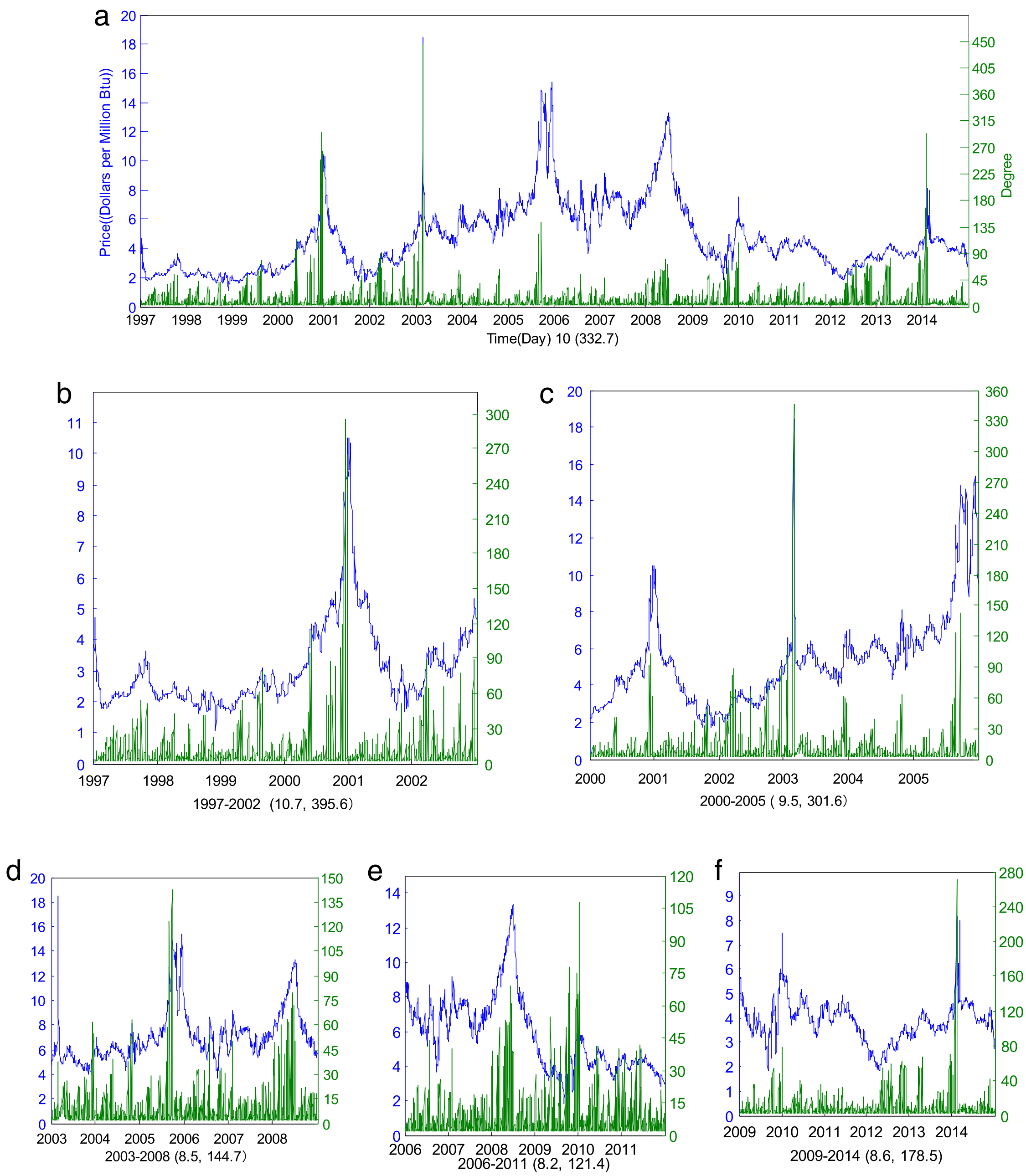


Fig. 3. Natural gas spot price and the corresponding degree in both the overall network (a) and five local networks (b–f). Natural gas spot price series is in blue (Dollars per Million Btu) and the degree for every node in the corresponding visibility network is in green. The mean and variance of degrees are presented in parentheses under each window's plot. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.2.3. *Small-world network*

In order to further reveal the characteristics of the fluctuations of North American natural gas prices time series, we explore the existence of small-world characteristics from another point of view. We studied the change of the average shortest path length with the increase of the number of nodes in visibility graph network. L is the average shortest path length, N is the number of nodes. If there is linear relationship between L and logarithm of N, then we have $L = a + b \ln N$, the network is of small-world properties. Inversely, a network may be considered as a big world network when L has linear relationship with N. In Table 2, a, b, R^2 represent intercept, slope and fitting accuracy respectively. We found that there are obvious linear relationships between the average shortest path length L and the size of the network $\ln N$.

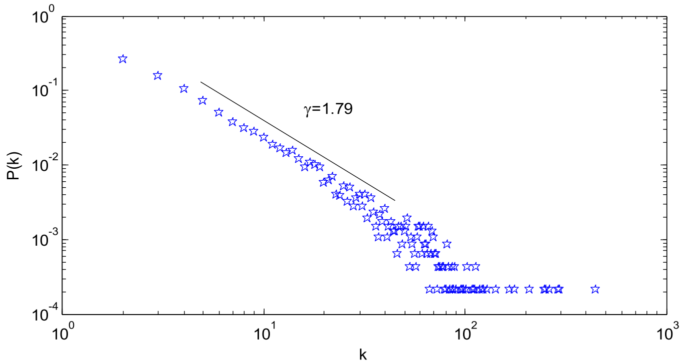


Fig. 4. Degree distribution of the overall NGP-VGN.

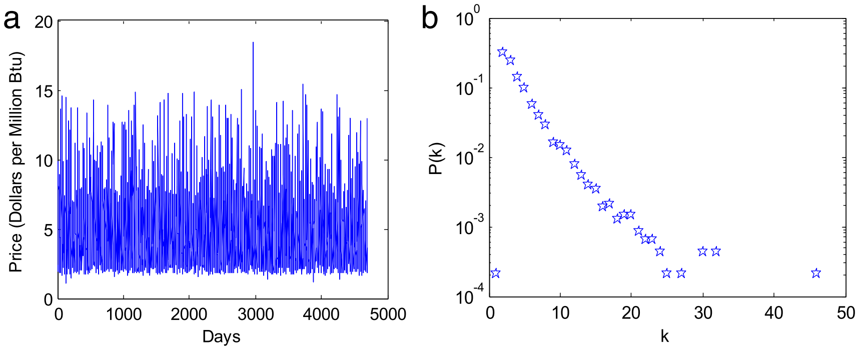


Fig. 5. The overall random rearranged natural gas price series (a) and degree distribution of its visibility graph (b).

Table 2
Relationship between L and $\ln N$.

Time windows	a	b	R^2	Significance
1997–2014	−0.97	0.67	0.97	Significant
1997–2002	−1.47	0.75	0.96	Significant
2000–2005	2.90	0.19	0.26	Non-significant
2003–2008	−0.86	0.61	0.95	Significant
2006–2011	1.68	0.34	0.88	Significant
2009–2014	−0.40	0.67	0.90	Significant

To further test whether it is a small-world network, Fig. 6 shows the changes of the average shortest path length from the overall NGP-VGN to the random rearranged overall NGP-VGN. As we can see, the rearranged NGP-VGN is of big-world features which belongs to regular graphs. The different growing law of the average shortest path length between the original and rearranged networks means that, price fluctuations of the original time series are correlated. Fluctuations of the overall natural gas price are not random, but interrelated. For the overall NGP-VGN, the small-world characteristics can be explained by hub repulsion. In the visibility graphs of the original series, hubs corresponding to the highest values are not hidden by neighboring nodes, but in graphs of the random rearranged series, hubs are hidden and lose their original effects [16]. From the view of network growth, the small-world network means that in the process of growth, the newly added nodes choose preferential attachment instead of random links [17]. It indicates that fluctuations in the overall NGP-VGN are not random, but are attracted, restricted or influenced by previous prices. Newly added nodes would be influenced by historical nodes, and mostly influenced by hubs. Except for window 2000–2005, the price fluctuations in the other four local windows also have such characteristics. Hence, we specifically observed window 2000–2005, and found that, L and $\ln N$ have a linear relationship at the beginning. However, from the 540th node, L fall as the growth of $\ln N$. This may be caused by sudden appearance of a few hubs which shortened the average path length of the entire network.

From the 1080th node, L continue to increase with the growth of $\ln N$. Therefore, this should be caused by the selection of window size. Hence, the characteristics of natural gas price fluctuations can be explained well by the visibility algorithm. We also observe the change range of average shortest path length of the original local windows in Figs. 7–11. The range of window 2003–2008 is quite short, from 2.2 to 3.8, which can be due to the strong correlation of price fluctuations and the close connections between nodes. With an initial average shortest path of 2.2, hubs may be located in the front of this

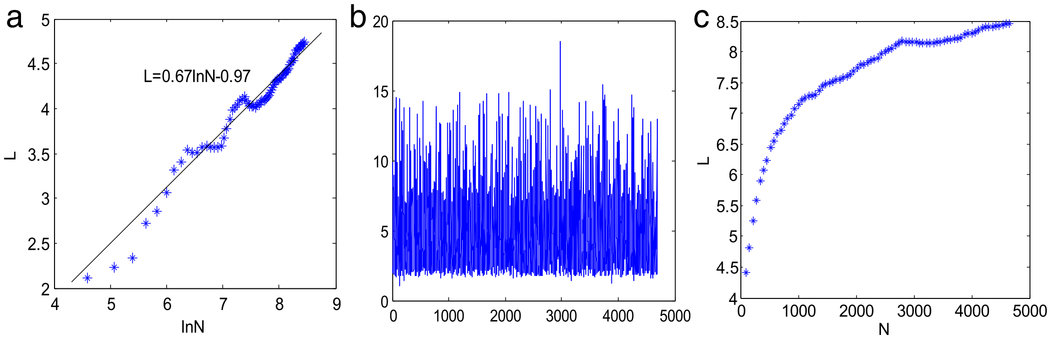


Fig. 6. Original and rearranged average shortest path length for the overall window. (a) The average shortest path length of the overall NGP-VGN; (b) The overall random rearranged series; (c) The average path shortest length of the overall random rearranged NGP-VGN.

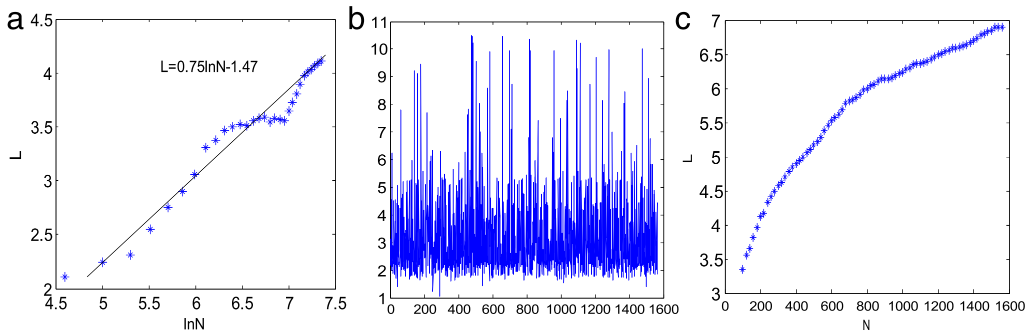


Fig. 7. Original and rearranged average shortest path length for window 1997–2002. (a) The average shortest path length of the original NGP-VGN; (b) The random rearranged series; (c) The average path shortest length of the random rearranged NGP-VGN.

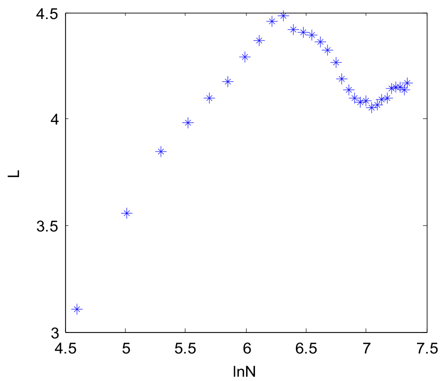


Fig. 8. Average shortest path length of the NGP-VGN for window 2000–2005.

window. The window 1997–2002 has similar situation. Change range of average shortest path length in other three windows all stay between 3 and 4.6. We can therefore say that, the relevance of price fluctuations in these windows is similar.

3.2.4. Community structure

Generally, nodes of this network can be divided into communities. Nodes connect closely within a community whereas sparse connections exist between different communities. The connections in visibility network based on the visibility of nodes, that is, nodes in a cycle have good visibility to each other. Therefore, cycles in time series convert to communities in visibility network. Due to the large span and complicated calculation of the overall time series, we only detected the community structure of the five local time windows by the Louvain Method. The range of the local NGP-VGN is adequate to capture the structure of natural gas prices. The results of the detection are shown in Fig. 12 where different communities are marked in different colors. The number of communities is in parentheses under the plot of each window. The number of nodes in one community represents the size of the community. The fluctuation mechanism of natural gas price can be seen by observing hubs and their divisions in communities. Hubs are identified using algorithm in Section 3.2.1, and their

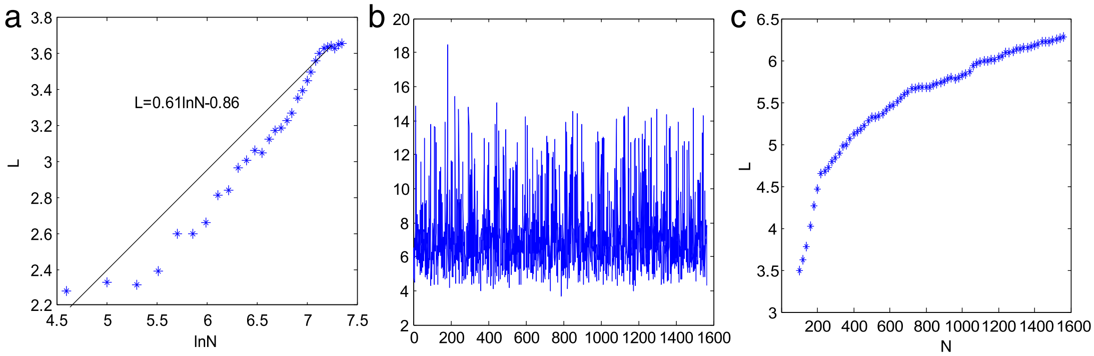


Fig. 9. Original and rearranged average shortest path length for window 2003–2008. (a) The average shortest path length of the original NGP-VGN; (b) The random rearranged series; (c) The average path shortest length of the random rearranged NGP-VGN.

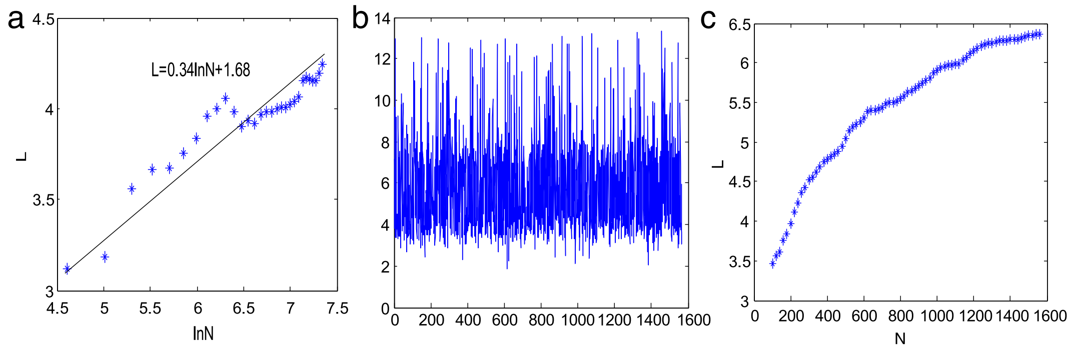


Fig. 10. Original and rearranged average shortest path length for window 2006–2011. (a) The average shortest path length of the original NGP-VGN; (b) The random rearranged series; (c) The average path shortest length of the random rearranged NGP-VGN.

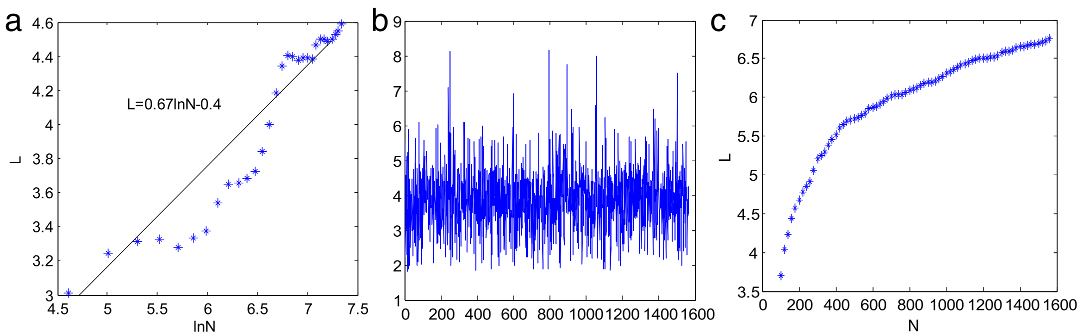


Fig. 11. Original and rearranged average shortest path length for window 2009–2014. (a) The average shortest path length of the original NGP-VGN; (b) The random rearranged series; (c) The average path shortest length of the random rearranged NGP-VGN.

Table 3
The corresponding events and the number of big communities which are connected to hubs.

Hubs	Price	Degree	Events	Communities
2000/12/11	9.96	295	Economic bubbles	2 big communities
2003/02/25	18.48	346	The Iraq war	1 big communities
2005/09/22	14.84	143	Hurricane Katrina	0 big communities
2008/06/06	12.71	80	Financial crisis	2 big communities
2010/01/07	7.51	108	Seasonal change	0 big communities
2014/02/05	8.12	271	Unbalance of supply and demand	1 big communities

statistical characteristics in communities are shown in Table 3. Compare to Fig. 13, except for node September 22, 2005 and January 7, 2010, other hubs all in large communities.

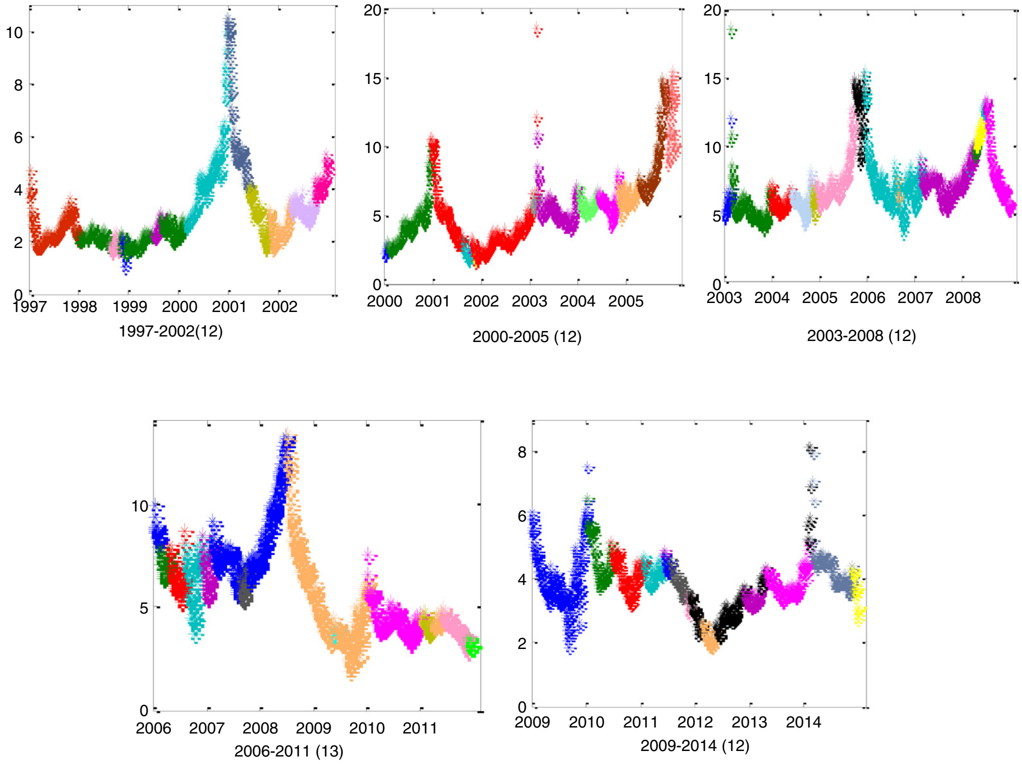


Fig. 12. The communities in the NGP-VGN. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

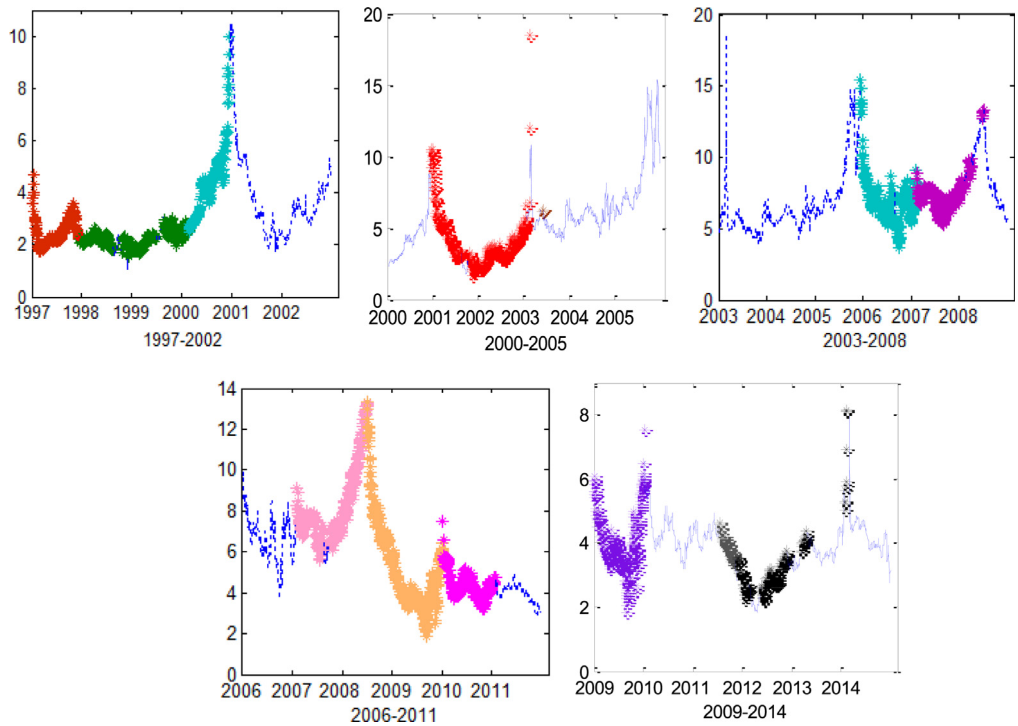


Fig. 13. The large communities with more than 250 nodes.

Typically, node June 6, 2008 connects two large communities. The subprime crisis in 2007, after a year of turbulence, rapidly evolved into an international financial crisis. This is rare, considering its large scale, long duration and serious damage. The global economy then, rapidly turn from inflation to deflation. According to the community structure, we realize the huge influence of inflation on natural gas prices in subprime crisis, and the falling scope of gas prices caused by economic recession in the financial crisis from the plot of window 2006–2011. In addition we find that the corresponding time series of some communities are not continuous. The reason is that, big communities at time series mingled with some small communities. For example, the range of communities connected to node February 5, 2014 is from 2011/7/21 to 2014/11/24, but there are several intervals. This shows that, the influencing range of hubs is not only simply around itself, but very wide and the emergence of a hub has a long incubation period. There are many factors to form a cycle of price fluctuations. Contrast to the seasonal change, the relationship between natural gas prices and weak domestic demand caused by the economic recession is more closely and directly. Therefore, through the community structure, we can find cycles of time series and the impact range of hubs.

4. Conclusions

In this paper, we studied the evolution mechanisms of North American natural gas market by using visibility graph algorithm. The analysis has demonstrated that the North American natural gas price is a long-range anti-persistence fractal time series. To better analyze its fluctuation characteristics, five 6-year windows are chosen, and five local NGP-VGNs are generated, respectively. With the analysis of degree sequence, we found that, nodes with large degree are not a simple overall or local maximum, but have huge impact on neighboring nodes, such as the Iraq war in 2003. In addition, the North American NGP-VGN has scale-free properties. This means that, the impact of majority nodes to price fluctuation is small, with a few nodes having large degrees being influential. The influence of hubs in the later three local networks is less than the others. This is because, price volatility tends to be affected by multiple factors, such as major events and short-term supply and demand, etc. We also analyzed the average shortest path length of the overall and the five local NGP-VGNs and their relationship with network scale. We found that, there exists small-world characteristics. The identification of the community structure shows that, cycles in time series can be converted to communities in the corresponding visibility graph network with hubs often connecting to large communities. This means that, the impact range of hubs is large, or price fluctuations of a long period lead to hubs.

The analysis above is only for the North American natural gas market where the spot price fluctuations are mainly determined by the forces of demand and supply, or major geo-economic events. Presently, the extent of deregulation of Europe and Asia markets is not high, and North America will seek markets in Asia, which will promote the formation of a unified natural gas market. Therefore, it is of great importance to understand the mechanism of spot price fluctuations of natural gas in North America. This will benefit other countries to avoid the systematic risk and improve their natural gas pricing system.

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References

[1] A. Shahmoradi, Returns and volatility in the NYMEX Henry hub natural gas futures market, Opec Rev. 30 (3) (2006) 171–186.
[2] L.T. Orlowski, From pit to electronic trading: Impact on price volatility of US Treasury futures, Rev. Financ. Econ. 25 (2015) 3–9.
[3] M.H. Chen, Understanding world metals prices—Returns, volatility and diversification, Resour. Policy 35 (3) (2010) 127–140.
[4] T. Kanamura, A supply and demand based volatility model for energy prices, Energy Econ. 31 (5) (2009) 736–747.
[5] B.R. Auer, Daily seasonality in crude oil returns and volatilities, Energy Econ. 43 (2) (2014) 82–88.
[6] H.V. Goor, B. Scholtens, Modeling natural gas price volatility: The case of the UK gas market, Energy 72 (7) (2014) 126–134.
[7] An H, W. Zhong, Y. Chen, et al., Features and evolution of international crude oil trade relationships: A trading-based network analysis, Energy 74 (5) (2014) 254–259.
[8] Lacasa Lucas, Luque Bartolo, Ballesteros Fernando, Luque Jordi, Juan Carlos, From time series to complex networks: the visibility graph, PNAS 105 (13) (2008) 4972–4975.
[9] L. Yu, Visibility graph network analysis of gold price time series, Physica A 392 (16) (2013) 3374–3384.
[10] Y. Yang, J. Wang, H. Yang, J. Mang, Visibility graph approach to exchange rate series, PhysicaA 388 (20) (2009) 4431–4437.
[11] B. Zhang, J. Wang, W. Fang, Volatility behavior of visibility graph EMD financial time series from Ising interacting system, Physica A 432 (2015) 301–314.
[12] N. Wang, D. Li, Q. Wang, Visibility graph analysis on quarterly macroeconomic series of China based on complex network theory, Physica A 391 (24) (2012) 6543–6555.
[13] E. Zhuang, M. Small, G. Feng, Time series analysis of the developed financial markets' integration using visibility graphs, Physica A 410 (2014) 483–495.
[14] V.D. Blondel, J.L. Guillaume, R. Lambiotte, et al., Fast unfolding of communities in large networks, J. Stat. Mech. Theory Exp. 30 (2) (2008) 155–168.
[15] N. Xu, P. Shang, S. Kamae, Modeling traffic flow correlation using DFA and DCCA, Nonlinear Dynam. 61 (1–2) (2010) 207–216.
[16] C.M. Song, S. Havlin, H. AMakse, Origins of fractality in the growth of complex networks, Nat. Phys. 2 (4) (2006) 275–281.
[17] V. Alexei, P.S. Romualdo, V. Alessandro, Large-scale topological and dynamical properties of the Internet, Phys. Rev. E (3) 65 (6 Pt 2) (2002) 104–130.