Energy Economics 71 (2018) 201–212

Contents lists available at ScienceDirect

Energy Economics

journal homepage: www.elsevier.com/locate/eneeco

A novel approach for oil price forecasting based on data fluctuation network

Minggang Wang [a,b], Lixin Tian [a,*], Peng Zhou [c]

[a] School of Mathematical Science, Nanjing Normal University, Nanjing 210042, Jiangsu, China
[b] Department of Mathematics, Taizhou College, Nanjing Normal University, Taizhou 225300, Jiangsu, China
[c] College of Economics and Management, Nanjing University of Aeronautics and Astronautics, Nanjing 210016, Jiangsu, China

ARTICLE INFO

Article history:
Received 19 June 2017
Received in revised form 14 February 2018
Accepted 23 February 2018
Available online 1 March 2018

JEL classifications:
C45
C53
Q47
C22
C02
C15

Keywords:
Time series
Complex network
Oil price
Prediction

ABSTRACT

Characterizing nonlinear time series using complex network science is a new multidisciplinary methodology. This paper puts forward a new time series prediction method based on data fluctuation network, named data fluctuation networks predictive model (DFNPM). The basic idea of the method is: first map time series into data fluctuation network and extract the fluctuation features of time series according to the topological structure of the networks, and then construct models with useful information extracted to predict time series. With Cushing, OK Crude Oil Future Contract 1 (Dollars per Barrel) and New York Harbor Regular Gasoline Future Contract 1 (Dollars per Gallon) as its sample data as well as DFNPM as its prediction model, the research makes a prediction on crude oil and gasoline futures prices from December 30, 2014 to February 26, 2015. A comparison is conducted between the result of the prediction and such traditional prediction models as grey prediction (GM) model, exponential smoothing model (ESM), autoregressive integrated moving average (ARIMA) model and radial basis function neural network (RBF) model, which shows that DFNPM performs significantly better than the above four traditional prediction models in both the direction and level of prediction.

1. Introduction

The fluctuation of oil price plays an important role in social economy. Therefore, the prediction of oil price has always been a hot research topic for scholars at home and abroad. Some oil price prediction methods are based on traditional econometric models. For instance, Xiang and Zhuang (2013) used an autoregressive integrated moving average (ARIMA) model to predic the Brent monthly crude oil price from November 2012 to April 2013. Nomikos and Andriosopoulos (2012) estimated the conditional mean and volatility of West TexasIntermediate (WTI) daily crude oil spot prices from December 9, 2000 to January 2, 2010, based on the generalized autoregressive conditional heteroskedasticity (GARCH) family models. Murat and Tokat (2009) used the random walk (RW) model to forecast oil price movements and crack spread futures. Mirmirani and Li (2005) used the vector autoregression (VAR) model to predict the US monthly oil price covering the period from January 1980 to November 2002. Lanza et al. (2005) used the error correction model (ECM) to predict the WTI and Brent weekly crude oil prices with the sample period from 1994 to 2002. Morana (2001) proposed a semiparametric approach to oil price forecasting, which allows one to forecast the entire oil price distribution at different time horizons, without requiring the specification of a structural model for the conditional mean of the oil price process. Other methods are based on artificial intelligence (AI) and can effectively distinguish random factors which traditional econometric models are unable to do. These AI methods can provide more accurate results for some situations. For example, Movagharnejad et al. (2011) introduced the artificial neural network (ANN) to forecast the quantitative data of crude oil prices over the period from January 2000 to April 2010. Chiroma et al. (2015) presented an evolutionary neural network (ENN) to predict the WTI monthly crude oil price data from May 1987 to December 2011. Khashman and Nwulu (2011) predicted the WTI weekly spot crude oil prices from January 03, 1986 to December 25, 2009, based on the SVR model. Similarly, Li and Ge (2013) predicted the crude oil prices from May 1994 to December 1995 based on an e-SVR model with dynamic errors correction. Xie et al. (2006) compared the support vector regression (SVR) with the ARIMA and back-propagation neural network (BPNN), and witnessed the superiority of the SVR in the prediction for the WTI monthly prices from January 1970 to December 2003. Li et al. (2013) predicted the WTI weekly data from January 4, 2008 to October 18, 2013 using least squares support vector machines

* Corresponding author.
E-mail addresses: tianlx@ujs.edu.cn (L. Tian), cemzp@nuaa.edu.cn (P. Zhou).

https://doi.org/10.1016/j.eneco.2018.02.021
0140-9883/

(LSSVM), and argued that the LSSVR outperformed the ARIMA, SVR and BPNN models. However, these AI models have their own weaknesses, e.g., parameter sensitiveness and potential over-fitting (Tang et al., 2012). Recently, the hybrid prediction methods have developed and become a predominant type for oil price forecasting. For instance, Wang et al. (2005) proposed the promising concept of decomposition and ensemble, and then a series of decomposition–ensemble learning paradigms have been developed for crude oil price forecasting. In a typical decomposition–ensemble model, three main steps are included, i.e., data decomposition for simplifying the complex data, individual prediction for each decomposed mode, and ensemble prediction for final prediction result (Tang et al., 2012; Yu et al., 2008; Liu et al., 2013; Zhang et al., 2008). Zhang et al. (2015) propose a hybrid method that combines ensemble empirical mode decomposition (EEMD), least square support vector machine particle swarm optimization (LSSVM-PSO), and the GARCH model to forecast crude oil prices, and find this hybrid method has a strong crude oil price forecasting capability.

As mentioned above, the researchers have developed many prediction models to carry out prediction on oil price. The past literatures have shown that oil price forecasting results are sensitive to the modeling sample interval selection, sample data frequency and sample structural breaks etc. (Xiang and Zhuang, 2013; Nomikos and Andriosopoulos, 2012; Murat and Tokat, 2009; Mirmirani and Li, 2005; Lanza et al., 2005; Morana, 2001; Movagharnejad et al., 2011; Chiroma et al., 2015; Khashman and Nwulu, 2011; Li and Ge, 2013; Xie et al., 2006; Li et al., 2013; Tang et al., 2012; Wang et al., 2005; Yu et al., 2008; Liu et al., 2013; Zhang et al., 2008, 2015). Up to now, oil price prediction remains an open question, for the main reason that on one hand, the fluctuation of oil price time series is affected by various factors in market, such as political environment, natural environment and personal psychology. The interaction and collision among different factors bestow oil price time series with features of strong noise, instability and invisible periodicity. On the other hand, there are more or less defects in the existing prediction methods. For example, prediction model construction from the perspective of traditional statistics should be based on the stability in a statistical sense, or it may produce relatively poor prediction results for nonlinear time series (Xiang and Zhuang, 2013; Nomikos and Andriosopoulos, 2012; Murat and Tokat, 2009; Lanza et al., 2005; Morana, 2001). Although artificial intelligence (AI) method can well handle nonlinear prediction, there are some downsides for the method like low convergence rate, difficulty in choosing parameters and high likelihood to fall into local minimum (Movagharnejad et al., 2011; Chiroma et al., 2015; Khashman and Nwulu, 2011; Li et al., 2013; Xie et al., 2006; Tang et al., 2012). Therefore, there are still many problems worth discussion in the field of oil price prediction.

The prediction of oil price is essentially a kind of time series forecasting problem. Time series prediction has been a classic issue in the field of time series research. At present, there are mainly three types of time series prediction methods. First, statistical method based on traditional measurement theories. From the perspective of statistics, time series prediction and analysis, in nature, is a process in which a series of data is arranged according to the fluctuation over time and random factors of time series are extracted by statistical method to find out the interdependent relationship among data. The relationship is expressed in mathematical language to predict future data fluctuation. There are still many economic time series prediction methods within the range of statistics, including random walk (RW) theory (Kac, 1947), moving average (MA) theory (Box and Pierce, 1970), autoregressive (AR) model (Dijk et al., 2002), autoregressive moving average (ARMA) model, autoregressive integrated moving average (ARIMA) model, autoregressive conditional heteroskedasticity (ARCH) model and generalized autoregressive conditional heteroskedasticity (GARCH) model (De Gooijer and Kumar, 1992; Makridakis, 1993). Second, intelligent computing method based on computer science. The intelligent computing method can effectively determine random and complicated factors which traditional statistical method is unable to find out. Generally speaking, prediction by intelligent computing method promises a more accurate result. The classic intelligent computing techniques include artificial neural network (ANN) (Moody and Darken, 1989), support vector machine (SVM) (Boser et al., 1992; Mika et al., 1999) and the evolutionary algorithm (EA) (Tay and Cao, 2002; Niu et al., 2010). Third, the hybrid prediction methods which combine the advantages of various kinds of single prediction methods. In terms of complicated and nonlinear data, a single prediction method can only take into consideration some major factors while has no way to cover comprehensive and effective information of time series change, thus leading to low accuracy of the prediction results. Therefore, the hybrid prediction method (Winkler, 1989; Wang, 2009; Wang et al., 2012) has attracted more and more attention because of its advantages in solving the problem. Actually, the hybrid prediction method is a process in which the hidden information of series to be predicted is subdivided into a series of components and different prediction methods are chosen for information extraction according to the features of the components. In this way, the uncertainty caused by a single method can be reduced, so as to improve the control level of the whole prediction process.

In fact, to ensure high accuracy of oil price prediction, it is a must to first draw out precisely the regular pattern of the fluctuation of oil price time series and then extracts effectively the useful information of the fluctuation. In recent years, extensive attention has been cast to the application of complex network theory to nonlinear time series analysis. Its major concept is to map the nonlinear time series into corresponding complex networks through certain algorithms and then draw out the regular pattern for the fluctuation of nonlinear time series through the typology of complex networks. A lot of studies show that the application of complex network theory can effectively help find out the characteristics of time series, thus giving rise to many new algorithms that map time series into complex networks, including visibility graph (VG) (Lacasa et al., 2008), pseudo-periodic time series transform algorithm (Xu et al., 2008), phase space reconstruction method (Zhang and Small, 2006) and coarse graining method of phase space (Wang et al., 2017). Currently, the researchers have introduced the time series complex network analysis technique to the field of energy economy to study the fluctuation features of energy price (Wang and Tian, 2016; Chen et al., 2010; An et al., 2014; Wang et al., 2016b, 2016a). For example, Chen et al. (2010) constructs the network of international oil price to find out the dynamics features of the network. An et al. (2014) discusses the autoregressive effects of the fluctuation of crude oil price time series. Wang et al. (2016a) construct a directed and weighted network for international crude oil and gasoline prices to analyze the fluctuation features of international crude oil and gasoline prices in different periods. The above mentioned studies, through making use of complex network theory to study the fluctuation features of energy price, yield many valuable results.

Based on the previous studies, this paper uses time series complex network analysis techniques to put forward a new prediction method for oil price. This method is based on that converts oil price fluctuation sequences into complex networks, so this method is called data fluctuation networks predictive model (DFNPM). The basic approach is: transform oil price fluctuation time series into a directed and weighted network through certain algorithms and extract fluctuation features of oil price according to the topological structure of the network, and then construct models with useful information extracted to predict time series. We organize the rest of this paper as follows. Section 2 provides a detailed description of how the proposed model was formulated. Section 3 describes and discusses the oil forecasting results. At the end of the paper we present our conclusions and propose possible future lines of research.

2. Model construction

By means of coarse graining method (Wang et al., 2016a) mapped oil price fluctuation series into a character string composed of five

characters {R, r, e, d, D} and constructed the directed and weighted network for crude oil and gasoline prices. In terms of crude oil and gasoline prices, the authors choose 7,680 sample data respectively, which construct 7,676 fluctuation modes. According to the construction method of fluctuation mode, there should have been $5^5 = 3125$ different fluctuation modes. However, the fact that there are respectively 1,178 and 1,439 different modes in the crude oil fluctuation network and gasoline fluctuation network, which indicates that the number of modes in practice is far less than that in the theory and many fluctuation modes will never exist in reality. Research (Wang et al., 2016a) also makes an analysis of the time distribution features for different fluctuation modes. The result shows that the total time for the existence of different fluctuation modes presents an approximately linear distribution feature. The feature indicates that as time goes by, the interval between the new and different modes will be longer, which means that there will be no new modes in a short period and the future mode should be one once appeared before. Based on such thought, we can make use of the transforming relationship among different modes to predict the one will appear in future, so as to achieve prediction goal.

Using time series complex network analysis techniques, we formulate data fluctuation network predictive model (DFNPM) for oil prices (see Fig. 1). There are four steps in the proposed DFNPM, i.e., construct the data fluctuation network, determine the target node, design the rules and formulate the forecast.

2.1. Step 1: construct the data fluctuation network

At present there are a variety of algorithms for mapping time series into complex networks, such as visibility graph (VG) (Lacasa et al., 2008), pseudo-periodic time series transform algorithm (Xu et al., 2008), phase space reconstruction method (Zhang and Small, 2006) and coarse graining method of phase Space (Wang and Tian, 2016) mentioned above. In this paper, we use the coarse graining algorithm for transformation (Wang et al., 2016a). The basic process is as follows: set the time series as $X(t), t = 1, 2, \cdots, M$, calculate the corresponding fluctuation ratio series $P(t)$ with $X(t)$, select the appropriate threshold r_0 for fluctuation ratio series symbolization, then get $S = [(M - L)/l + 1]$ fluctuation modes in which L represents the sliding window length, l the sliding step, record the fluctuation modes as FM_i, $i = 1, 2, \cdots, S$. Take each different fluctuation mode as the node, and construct the directed and weighted data fluctuation network according to the chronological order. Number each node in the data fluctuation network in time sequence and record as $v_i^{(t)}, i = 1, 2, \cdots, N$ in which N indicates the number of nodes in the data fluctuation network, $N \le S$. There is a certain quantitative relationship between the number of the node (N) and the selected sample data size (M). Take the time series of crude oil and gasoline futures prices selected in research (Wang et al., 2016a) as an example, adopt the above algorithm and select the threshold by two different methods, one of which is to select a fixed threshold r_0 (Wang et al., 2016a), and the formula is as follows:

$$r_0 = \frac{1}{M}\sum_{t=1}^{M}|P(t)| \tag{2.1}$$

In the formula, M represents a certain number and the threshold r_0 does not vary with the number of selected samples. The other method is to select a variable threshold r_m:

$$r_m = \frac{1}{m}\sum_{t=1}^{m}|P(t)| \tag{2.2}$$

Here, m represents the number of selected samples and the threshold r_m varies with m. The relation between the node number of crude oil price fluctuation network and the crude oil data size is shown in Fig. 2(a), the relation between the node number of gasoline price fluctuation network and the gasoline data size is shown in Fig. 2(b). The tangent lines represent the growth rate.

It can be seen that the growth patterns of crude oil and gasoline price network nodes have similar characteristics under two different threshold selection methods. When the sample data size reach a certain amount, the number of nodes will tend to be stable. With a variable threshold, for the crude oil price fluctuation network, the growth rate of nodes is 40.21% when the sample data size is within 2,000, 13.74% when the sample data size is between 2,000 to 4,000, 4.05% when the sample data size is between 4,000 to 6,000, and 2.21% when the sample data size is over 6,000. For the gasoline price fluctuation network, the growth rate of nodes is 49.84% when the sample data size is within 2,000, 22.42% when the sample data size is between 2,000 to 4,000, 5.00% when the sample data size is between 4,000 to 6,000, 4.79% when the sample data size exceeds 6,000. With a fixed threshold, for the crude oil price fluctuation network, the growth rate of nodes is 41.74% when the sample data size is within 2,000, 13.79% when the

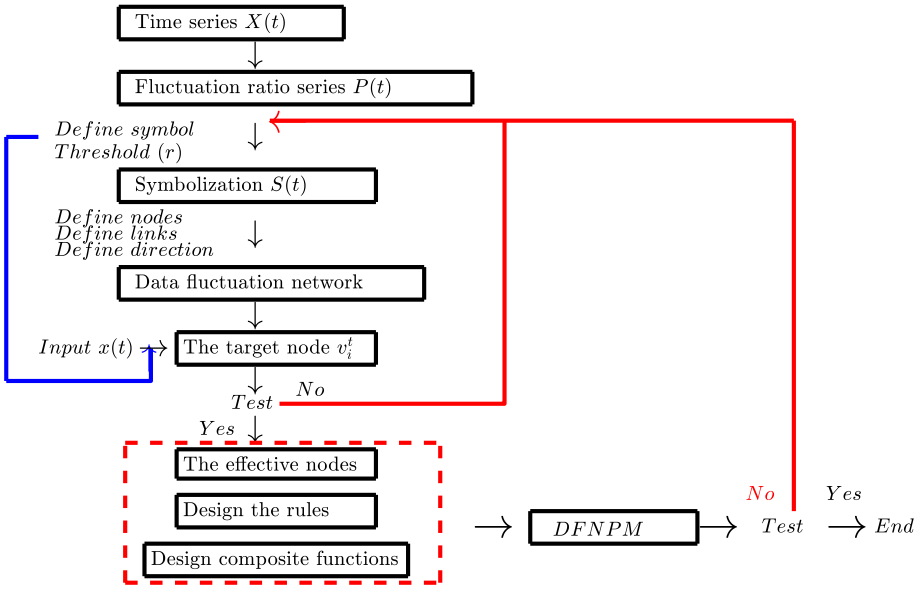

Fig. 1. The frame of data fluctuation network predictive model.

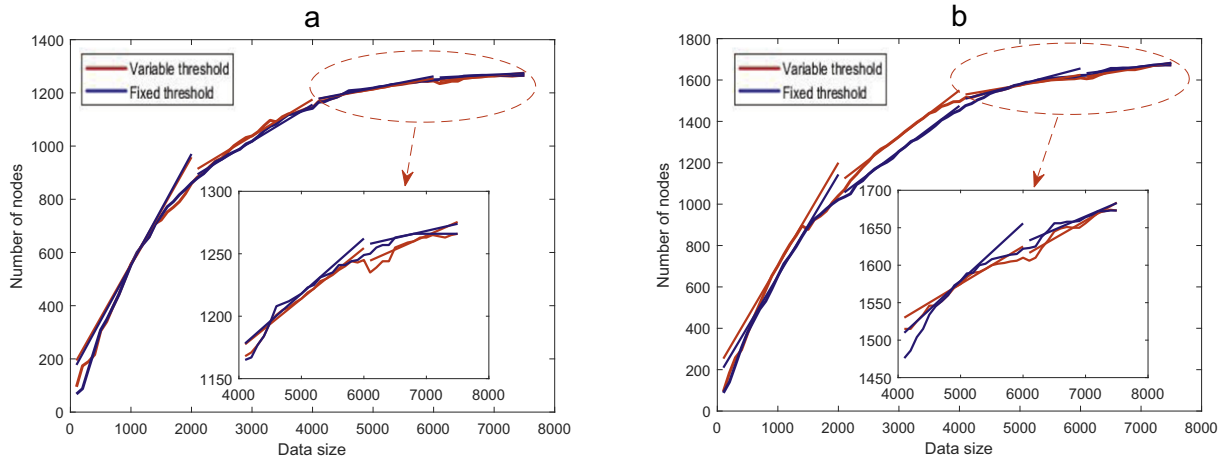

Fig. 2. The relation between the node number of oil price fluctuation network and oil price data size (a) crude oil (b) gasoline.

sample data size is between 2,000 to 4,000, 4.42% when the sample data size is between 4,000 to 6,000, and 1.14% when the sample data size exceeds 6,000; For gasoline price fluctuation network, the growth rate of nodes is 49.16% when the sample data size is within 2,000, 22.00% when the sample data size is between 2,000 to 4,000, 7.68% when the sample data size is between 4,000 to 6,000, and 3.57% when the sample data size exceeds 6,000. It is thus clear that when the sample data size reaches a certain amount, for both the crude oil price fluctuation network and the gasoline price fluctuation network, the number growth of nodes in the network will slow down gradually, which means that in short term, there will be no new nodes, and in this way it lays the foundation for the following prediction.

Note that the choice of threshold will affect the topological structure of the data fluctuation network, the change of which affects the effective data extraction, and thus affect the model's prediction accuracy. In practical application, we can use the method of test analysis to determine how to select the optimal threshold according to the known sample data. The specific approach is as follows: determine a threshold r_0 from the sample data set according to Eq. (2.1), then select the threshold r_i in the vicinity of r_0, and calculate respectively the corresponding loss function $G_k(r_i)$ with different r_i thresholds. The constructed optimization model is as follows:

$$\begin{aligned} &\min\ G(r_i) = \sum_k \omega_k g_k(r_i) \\ &s.t.\ \ g_k(r_i) \le g_k(r_0) \end{aligned} \tag{2.3}$$

Then obtain through calculation the threshold r_i that meets the prediction accuracy requirements.

2.2. Step 2: determine the target node $v_i^{(t)}$

Determine the corresponding network node of the latest array and its location information in the data fluctuation network according to the network construction method. For example, we use five characters {R, r, e, d, D} to represent the fluctuation sequence, let $L = 5$, and $l = 1$ and denote the node at time t to be $v_i^{(t)}$, where $t = 1, 2, \ldots, S$, $S = M - L + 1$, and $i = 1, 2, \ldots, N$. Since the data fluctuation network is a directed network, with the exception of the first and the last nodes every node has an in-neighbor node and out-neighbor node. Using the construction method of the data fluctuation network (see step 1), we see two types of connection between node v_i^s and its out-neighbor nodes: (i) If the mapped symbol series of the time series is {eddRrRDDRr}, then the corresponding node of the latest array is $v_6^6 =$ RDDRr, Fig. 3(a) shows the network structure. Here the number of the nodes is equal to the number of the fluctuation modes, i.e. $N = S$, the target node v_6^6 has no out-neighbor node. (ii) If the mapped symbol series of the time series is {ddRrRDedRrRD}, then the corresponding node of the latest array is $v_2^8 =$ dRrRD, Fig. 3(b) shows the network structure. Here the number of the nodes is less than the number of the fluctuation modes, i.e. $N < S$, the target node v_2^8 has out-neighbor node(s). Accurately identifying the location of the latest array in the network is the basis for the prediction.

In practical application, we wish the corresponding network node of the latest array could be the situation in Fig. 3(b). In fact, according to the data fluctuation network construction method (see step 1), if the sample data size is sufficient, the corresponding network node of the latest data array will be the situation shown in Fig. 3(b). If the number of samples is insufficient, the following two ways to improve the data fluctuation network are recommended to obtain the network structure shown in Fig. 3(b). One way is to reduce the use of symbols in the coarse-graining process, such as adopting three kinds of characters to conduct coarse graining on the fluctuation ration series; the other way is to use combination of fewer characters during the construction of the fluctuation mode, such as adopting 3-character combination as a fluctuation mode. Through these two methods, small sample data size can also be mapped into a better data fluctuation network.

2.3. Step 3: design the rules to predict the next node $v_{i\to j}^{(t+1)}$

From step 2, the target node $v_i^{(t)}$, $t = S$ only has two different types, we design the following rules for these two different situations.

(1) If $v_i^{(t)}$ has no out-neighbor node in the data fluctuation network (as shown in Fig. 3(a)), that is, $i = N$, then the future node that appears at $t + 1$ can be estimated according to the trend extrapolation method. That is, if $v_i^{(t)} = (s_1 s_2 s_3 s_4 s_5)$, then $v_{i\to j}^{(t+1)} = (s_2 s_3 s_4 s_5 s_5)$. In fact, in specific application, we can use methods in Step 1 and Step 2 to avoid such situation.

(2) If $v_i^{(t)}$ has out-neighbor nodes in the data fluctuation network (as shown in Fig. 3(b)), that is, $i < N$, then check in the network to find all the out-neighbor nodes of $v_i^{(t)}$. The set of all these out-neighbor nodes is

$$V_{i\to j}^{(t+1)} = \left\{ v_{i\to j_1}^{(t+1)}, v_{i\to j_2}^{(t+1)}, v_{i\to j_3}^{(t+1)}, \ldots, v_{i\to j_n}^{(t+1)} \right\},\ \ j_1, j_2, \ldots, j_n \in [1, N]$$

From the above analysis, we assert that the future node at $t + 1$ must be one of the elements in the set of $V_{i\to j}^{(t+1)}$. There are the following five common rules to determine the exact element.

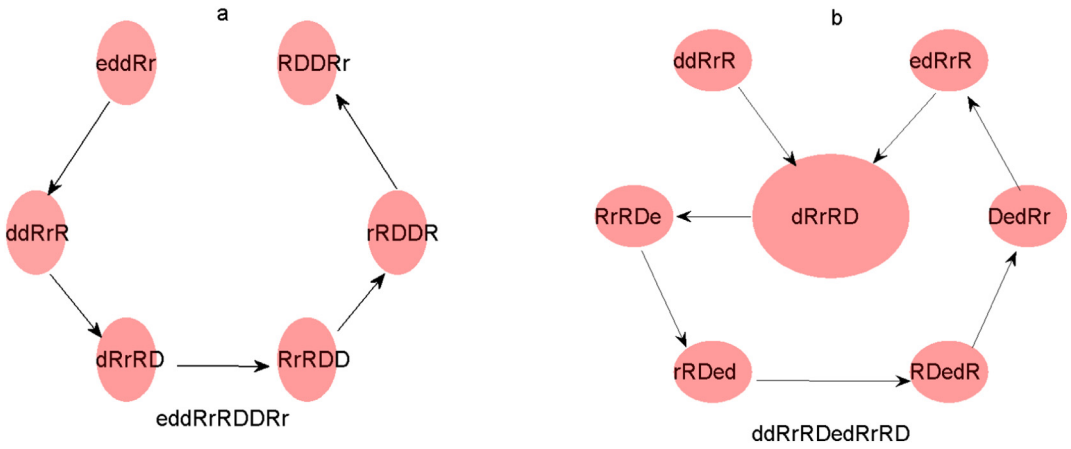

Fig. 3. The corresponding network node of the latest data array.

Rule I The new information priority principle, that is, select the element with the largest subscript from the set of $V_{i\to j}^{(t+1)}$ as the node at $t+1$, i.e., $v_{i\to j}^{(t+1)}, j = \max\{j_1, j_2, \ldots, j_n\}$;

Rule II The old information priority principle, that is, select the element with the smallest subscript from the set of $V_{i\to j}^{(t+1)}$ as the node at $t+1$, i.e., $v_{i\to j}^{(t+1)}, j = \min\{j_1, j_2, \ldots, j_n\}$;

Rule III The principle of the greatest node strength, that is, selects the element with the greatest strength from the set of $V_{i\to j}^{(t+1)}$ as the node at $t+1$;

Rule IV The principle of the second greatest node strength, that is, selects the element with the second greatest strength from the set of $V_{i\to j}^{(t+1)}$ as the node at $t+1$;

Rule V The principle of greatest connection strength with $v_i^{(t)}$, that is, selects the element with the greatest connection strength with $v_i^{(t)}$ from the set of $V_{i\to j}^{(t+1)}$ as the node at $t+1$;

Different prediction models can be obtained under different rules. In practical application, a variety of rules can be used together to build a prediction model with regular combination based on data fluctuation network. According to the actual situation and adopting the known sample data for testing, the optimal rule can be determined.

2.4. Step 4: design the composite function to build the DFNPM for prediction

The traditional prediction models can be expressed as follows:

$$\hat{X}_{t+h} = f(X_t) + \varepsilon_t \tag{2.4}$$

where, X_t represents the data at t, that is, $X_t = \{x_{t-1}, x_{t-2}, \cdots, x_{t-\tau}\}$ in which τ is the number of lag phase, h the prediction scale and ε_t the prediction error. In fact, the prediction model predicts the future data at $t+h$ based on data in the early τ stage of t phase.

The model built in this paper is as follows:

$$\begin{cases} \hat{P}_{t+h} = f\left(P_{i\to j}^{t}\right) + \varepsilon_t, \\ \hat{X}_{t+h} = X_t + X_t \hat{P}_{t+h} \end{cases} \tag{2.5}$$

where, $\hat{P}$, $\hat{X}$ represent the prediction for P and X, respectively. X_t stands for the data at t, h is the prediction scale and ε_t is the prediction error, $P_{i\to j}^{t}$ is the set of fluctuation rate corresponding to node $v_{i\to j}^{t}$, $f(x)$ is a composite function. It can be seen that the prediction model built in this paper takes the effective information extracted with the data fluctuation network as the input variables. The effective information may be data closer to the time t, or data far away from it, which is different from the traditional prediction models.

In the simplest case, if the composite function $f(x)$ is the rule given in Step 3, then DFNPM-I, DFNPM-II, DFNPM-III, DFNPM-IV, DFNPM-V and the DFNPM-H model under combination rules can be constructed. Other combination rules can also be defined based on other network topology properties for a new prediction model. Since all the prediction model series are obtained based on the data fluctuation network, they can be named as the DFNPM family models.

In summary, we use five characters {R, r, e, d, D} to represent the fluctuation sequence, let $L = 5$, and $l = 1$, then the calculation process of DFNPM is shown in Fig. 4.

3. Empirical analysis

We select the daily prices of *Cushing, OK Crude Oil Future Contract 1 (Dollars per Barrel)* and *New York Harbor Regular Gasoline Future Contract 1 (Dollars per Gallon)* from January 7, 1985 to December 29, 2014 published by the Energy Information Administration (EIA) (http://www.eia.gov/) as sample data, and then predict the daily prices of crude oil and gasoline futures from December 30, 2014 to July 21, 2015 with DFNPMs. In order to test prediction effects, we use the following two loss functions to measure these models' level prediction accuracy.

Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{x_t - \hat{x}_t}{x_t}\right| \tag{3.1}$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{t=1}^{N}(\hat{x}_t - x_t)^2}{N}} \tag{3.2}$$

where $\hat{x}_t$ and $x_t (t = 1, 2, \cdots, N)$ are predicted value and real value at time t respectively, and N is the data size of testing set. Loss function MAPE reflects the mean absolute relative error of prediction models, while loss function RMSE shows those models' standard deviation. These two indicators can be used to measure prediction accuracy. The smaller the values of MAPE and RMSE are, the more accurate the models are in making predictions. Among many prediction questions, we are more interested in tendencies (upward, stable or downward) in data fluctuations, so we use the following indicators to measure the directional prediction accuracy.

$$\begin{aligned} D_{stat} &= \frac{1}{N}\sum_{t=1}^{N} a_t \\ a_t &= \begin{cases} 1, (x_{t+1} - x_t)(\hat{x}_{t+1} - x_t) \geq 0 \\ 0, \quad otherwise \end{cases} \end{aligned} \tag{3.3}$$

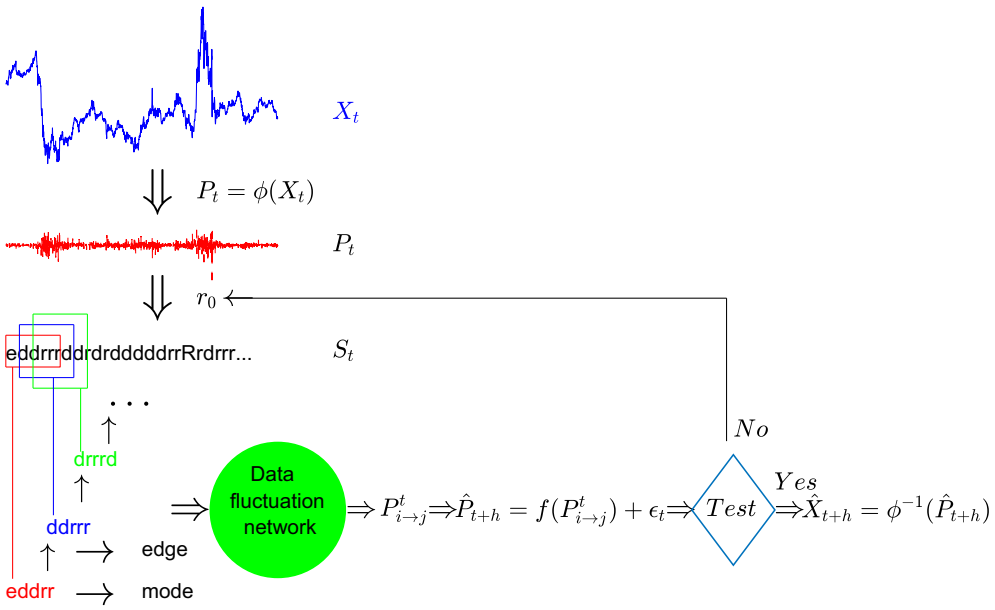

Fig. 4. The calculation process of DFNPM.

The closer the value of Dstat is to 1, the higher the accuracy of the directional prediction of the models, and the closer the Dstat value is to 0, the lower the accuracy of their directional predictions.

We use the Diebold-Mariano (DM) statistic (Yu et al., 2014) to measure the differences in the predictive accuracies of the forecasting models. Here we set the loss function to the mean square prediction error (MSPE). The null hypothesis is that the MSPE value of the tested model is not lower than that of the benchmark model. The DM statistic is defined

$$DMS = \frac{\overline{D}}{\sqrt{V_{\overline{D}}/M}}, \tag{3.4}$$

where

$$\overline{D} = \frac{1}{M}\sum_{t=1}^{M} d_t, d_t = (x_t - \hat{x}_{test,t})^2 - (x_t - \hat{x}_{bench,t})^2, V_{\overline{D}} = \gamma_0 + 2\sum_{q=1}^{\infty}\gamma_q, \gamma_q = \mathrm{cov}(d_t, d_{t-q}).$$

$\hat{x}_{test,t}$ and $\hat{x}_{bench,t}$ are the predicted values for x_t calculated by the tested model and its benchmark model, respectively, at time t.

3.1. Evolution of prediction accuracy with sample data size

As mentioned above, the prediction models we have formulated in this paper use effective information extracted from data fluctuation networks as the input variable, so their prediction accuracy depends not only on the reliability of collected information, but also on the reasonability of the function selected to synthesize effective information. The extraction of effective information is largely dependent on the information volume of sample data. In this part, we figure out the relations between prediction accuracy and sample data size with the same composite functions. We use the prices of crude oil and gasoline futures from January 7, 1985 to December 29, 2014 as training sample data, and use the prices of crude oil and gasoline futures from December 30, 2014 to July 21, 2015 as testing sample data. We use Eq. (2.1) to calculate fixed threshold value r_0. The results show that r_0 for crude oil and gasoline futures are 0.0166 and 0.0174 respectively. Allow sample size range from 100 to 7500, and then establish prediction models DFNPM-I, DFNPM-II, DFNPM-III, DFNPM-IV and DFNPM-V. Use these models to make predictions and Eq. (3.1), Eq. (3.2) and Eq. (3.3) to measure the level and directional prediction accuracy. Then we can draw the evolution figure of prediction accuracy of prices of crude oil and gasoline varying with sample size, as shown in Fig. 5(a, b, c, d, e, f).

It can be seen that in Fig. 5, under each of these DFNPMs, both the level accuracy indicators MAPE and RMSE move downward and then gradually go stable, while the direction accuracy indicator Dstat goes upward and then turns stable. Such tendencies indicate that both the level and direction prediction accuracies of the models improve as sample size increases. A closer look at results of crude oil price prediction in Fig. 5(a) shows that when sample size reaches 4000, the mean value of MAPE of the five prediction models decreases from 0.0445 to 0.0374. In other words, under indicator MAPE, the prediction accuracy of these models can rise by an average of 15.83 percentage points. When sample size is above 4000, the mean MAPE values of the five models are: 0.0415, 0.0359, 0.0352, 0.0387 and 0.0358. That is, from the perspective of accuracy indicator MAPE, we can rank the prediction accuracy of the five models from high to low as: DFNPM-III, DFNPM-V, DFNPM-II, DFNPM-IV, DFNPM-I. As shown in Fig. 5(b), when sample size reaches 4000, accuracy indicator RMSE also displays a rapid downward tendency and the mean RMSE value of the five prediction models drops from 2.7983 to 2.1983. That is, from the perspective of accuracy indicator RMSE, the prediction accuracy of the models can improve by 21.60 percentage points. When sample volume is above 4000, the mean RMSE values of the five models are: 0.0415, 0.0359, 0.0352, 0.0387 and 0.0358. In other words, under accuracy indicator RMSE, the descending order of the prediction accuracy of the five models is: DFNPM-III, DFNPM-V, DFNPM-II, DFNPM-IV, DFNPM-I. As shown in Fig. 5(c), when sample size reaches 4000, accuracy indicator Dstat shows a rapid upward tendency and the mean Dstat value of the five prediction models increases from 0.5329 to 0.5737. That is, from the perspective of accuracy indicator Dstat, the prediction accuracy of the models can improve by 7.64 percentage points. When sample size is above 4000, the mean values of accuracy indicator Dstat of the five models are: 0.5147, 0.6125, 0.6647, 0.5206 and 0.6294, which indicates that under the direction accuracy indicator Dstat, the descending order of the prediction accuracy of the five models is: DFNPM-III, DFNPM-V, DFNPM-II, DFNPM-IV, DFNPM-I. As for the prediction of gasoline price, as shown in Fig. 5(d), when sample size reaches 3000, the level accuracy indicator MAPE displays a rapid downward tendency and the mean MAPE value of the five

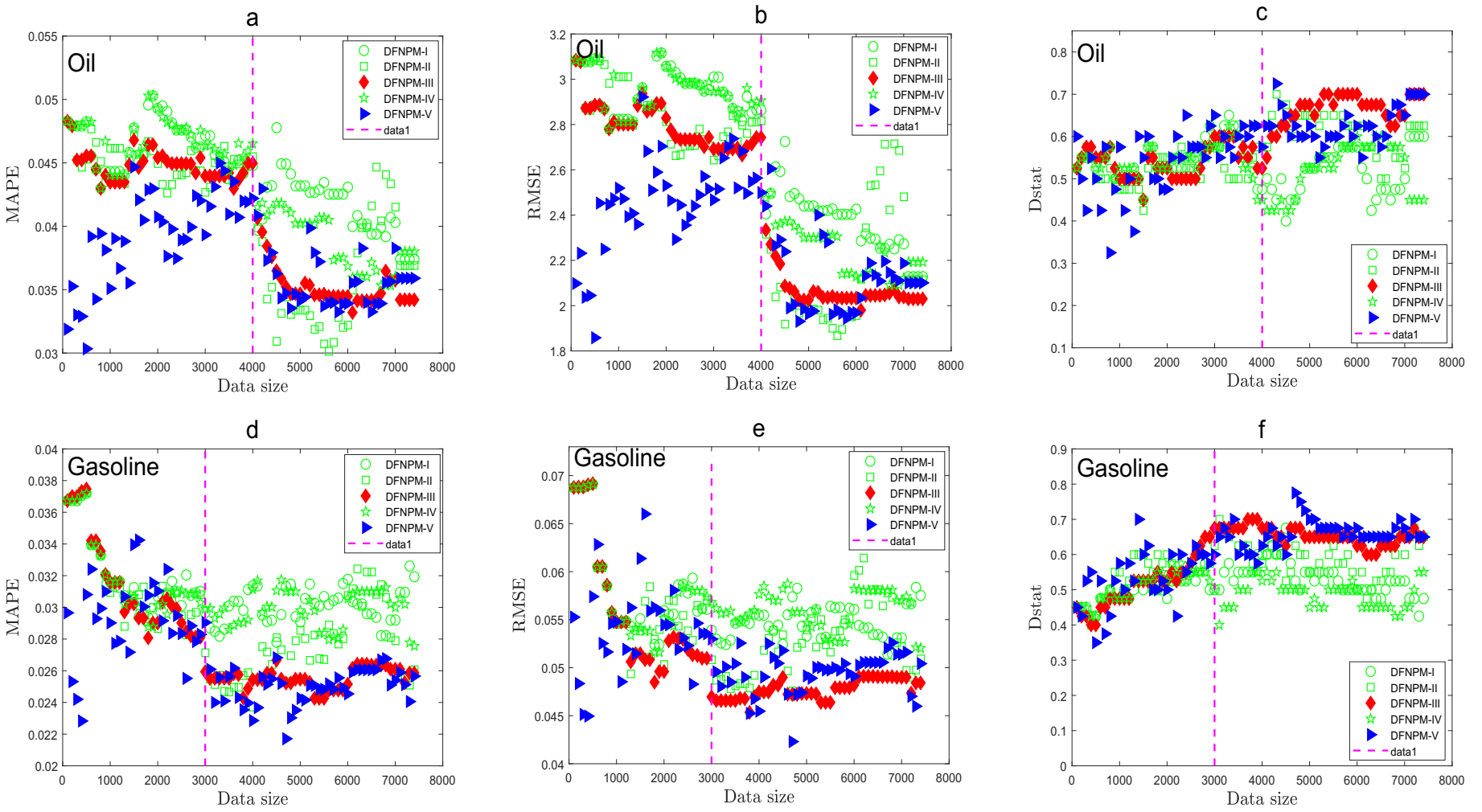

Fig. 5. Evolution of prediction accuracy with different data size (a) MAPE of crude oil price (b) RMSE of crude oil price (c) Dstat of crude oil price (d) MAPE of gasoline price (e) RMSE of gasoline price (f) Dstat of gasoline price.

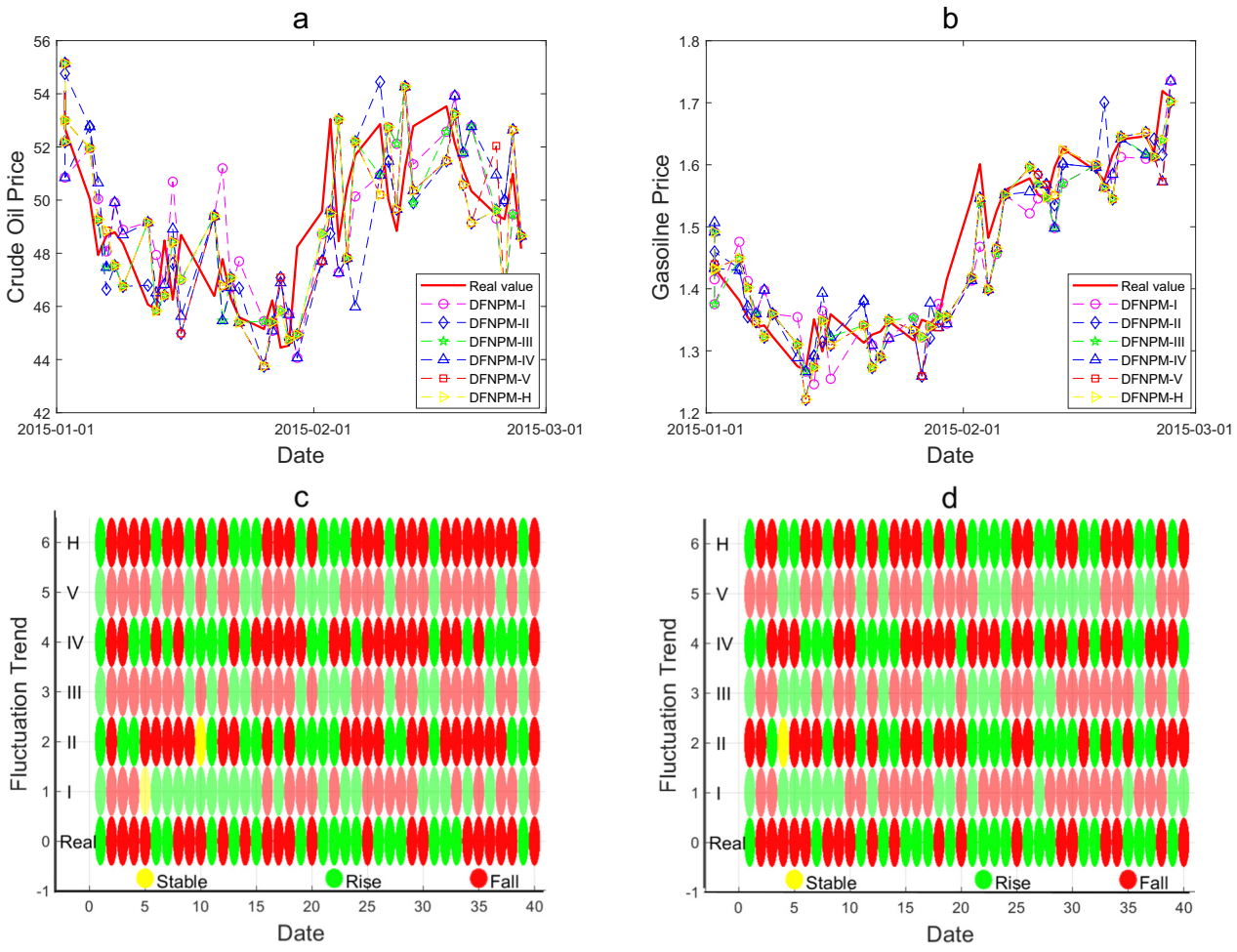

Fig. 6. A comparison of the prediction accuracy of different DFNPMs (a) the prediction accuracy of six DFNPMs of crude oil price (b) the prediction accuracy of six DFNPMs of gasoline price (c) the tendency prediction of six DFNPMs of crude oil price (d) the tendency prediction of six DFNPMs of gasoline price.

prediction models drops from 0.0301 to 0.0278. That is, from the perspective of indicator MAPE, the prediction accuracy of the models can improve by 7.63 percentage points. When sample size is above 3000, the mean Dstat values of the five models are: 0.0302, 0.0282, 0.0256, 0.0300 and 0.0251, which indicates that under indicator MAPE, the descending order of the prediction accuracy of the five models is: DFNPM-V, DFNPM-III, DFNPM-II, DFNPM-IV, DFNPM-I. As shown in Fig. 5(e), when sample size reaches 3000, the level accuracy indicator RMSE displays a rapid downward tendency as well and the mean RMSE value of the five prediction models drops from 0.0551 to 0.0525. That is, from the perspective of indicator RMSE, the prediction accuracy of the models can improve by 4.66 percentage points. When sample size is above 3000, the mean RMSE values of the five models are: 0.0548, 0.0539, 0.0481, 0.0561 and 0.0497, which indicates that under indicator RMSE, the descending order of the prediction accuracy of the five models is: DFNPM-III, DFNPM-V, DFNPM-II, DFNPM-I, DFNPM-IV. As shown in Fig. 5(f), when sample size reaches 3000, the direction indicator Dstat shows a rapid upward tendency and the mean RMSE value of the five prediction models rises from 0.5381 to 0.5812. That is, from the perspective of the direction indicator Dstat, the prediction accuracy of the models can improve by 8 percentage points. When sample size is above 3000, the mean Dstat values of the five models are: 0.5272, 0.5794, 0.6449, 0.4846 and 0.6699, which shows that under indicator Dstat, the descending order of the prediction accuracy of the five models is: DFNPM-V, DFNPM-III, DFNPM-II, DFNPM-I, DFNPM-IV. In a word, as sample size gets larger, the accuracy of DFNPMs will gradually increase and then stay stable. An overall look at the predictions about oil prices time series shows that the prediction accuracies of DFNPM-V and DFNPM-III are higher than other three models, which is in line with the result of reference (Wang et al., 2016a) that the node strength of the fluctuation network for oil prices exhibits power-law distributions.

Table 1
The prediction accuracy of six DFNPMs of crude oil and gasoline price.

		DFNPM -I	DFNPM -II	DFNPM -III	DFNPM -IV	DFNPM –V	DFNPM -H
Crude oil	MAPE	0.0302	0.0335	0.0305	0.0353	0.0292	0.0286
	RMSE	1.8869	2.0542	1.7488	2.1517	1.7293	1.6789
	Dstat	0.5750	0.6250	0.7000	0.5000	0.6750	0.8000
Gasoline	MAPE	0.0320	0.0265	0.0239	0.0275	0.0227	0.0226
	RMSE	0.0601	0.0510	0.0466	0.0542	0.0451	0.0449
	Dstat	0.4500	0.6000	0.6500	0.5000	0.6500	0.8000

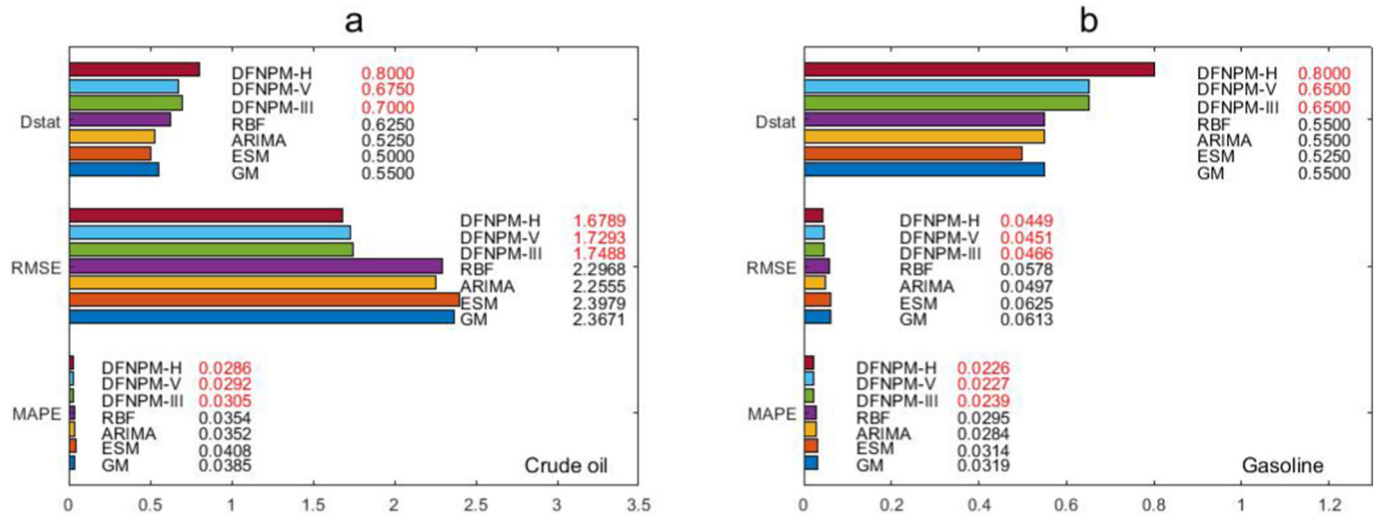

Fig. 7. The prediction accuracy of seven prediction models of oil prices (a) crude oil (b) gasoline price.

3.2. A comparison of the prediction accuracy of different DFNPMs with the same sample size

Selecting the prices of crude oil and gasoline from February 12, 1985 to December 29, 2014 (a total of 7500 data items) as sample data, we build six models, DFNPM-I, DFNPM-II, DFNPM-III, DFNPM-IV, DFNPM-V and DFNPM-H, the composite of DFNPM-III and DFNPM-V, to predict prices of crude oil and gasoline from December 30, 2014 to February 26, 2015. The prediction results of the six models are shown in Fig. 6(a, b). People tend to care more about how crude oil and gasoline prices fluctuate over time. Despite that many existing models are able to make relatively accurate predictions for prices, their predictions about the tendency of price fluctuations are hardly satisfying. In order to test how effective the six models are in predicting tendencies in price fluctuations, we draw two figures, Fig. 6(c, d), to compare estimated tendencies in price fluctuations with the real tendency.

As we can see in Fig. 6(a, b), fluctuation tendencies in crude oil and gasoline prices projected by six DFNPM models are similar to the real trend, which suggests that it is feasible to build prediction models on the basis of data fluctuation network. Calculations of the models' prediction accuracy are shown in Table 1. As we can see in Fig. 6(a, b) and Table 1, different DFNPMs have different prediction effects. Among five single DFNPMs, DFNPM-III and DFNPM-V perform better than other three single models, while model DFNPM-H, the composite of DFNPM-III and DFNPM-V, is obviously superior to all single models in terms of prediction effects. From the perspective of direction prediction accuracy, DFNPM-H has 80% accuracy in predicting tendencies in crude oil and gasoline price fluctuations. As shown in Fig. 6(c), DFNPM-H predicts 12 of the 19 changes in price fluctuations that crude oil went through from December 30, 2014 to February 26, 2015. As shown in Fig. 6(d), DFNPM-H predicts 16 of the 21 changes in price fluctuations that gasoline went through from December 30, 2014 to February 26, 2015. Therefore, prediction models built on the basis of data fluctuation

Table 2
DM test results for DFNPMs and four benchmark models.

		DFNPM-V	DFNPM –H	GM	ESM	ARIMA	RBF
Forecasting crude oil prices	DFNPM -III	0.3874	0.6645	−1.8565	−2.2575	−1.1448	−1.0533
		(0.6497)	**(0.7449)**	**(0.03547)**	**(0.01483)**	**(0.1296)**	**(0.1493)**
	DFNPM -V		1.1587	−2.0797	−2.5265	−1.424	−1.4971
			(0.8732)	**(0.0221)**	**(0.0078)**	**(0.0812)**	**(0.0712)**
	DFNPM -H			−2.2644	−2.7465	−1.6159	−1.6357
				(0.0146)	**(0.0045)**	**(0.0571)**	**(0.0550)**
	GM				−0.5511	2.1373	0.5161
					(0.2923)	**(0.9806)**	**(0.6956)**
	ESM					1.3592	0.8787
						(0.9091)	**(0.8075)**
	ARIMA						−0.0729
							(0.4711)
Forecasting gasoline prices	DFNPM -III	0.8508	1.0344	−1.8582	−1.6601	−1.2340	−2.0670
		(0.8000)	**(0.8463)**	**(0.0354)**	**(0.0525)**	**(0.1123)**	**(0.0227)**
	DFNPM -V		0.2893	−2.2050	−1.9312	−1.8716	−2.5401
			(0.6130)	**(0.0167)**	**(0.0304)**	**(0.0344)**	**(0.0076)**
	DFNPM -H			−2.2509	−1.9642	−1.9068	−2.6008
				(0.0151)	**(0.0283)**	**(0.0320)**	**(0.0065)**
	GM				0.0539	0.8601	0.4394
					(0.5214)	**(0.8025)**	**(0.6686)**
	ESM					0.8114	0.3888
						(0.7890)	**(0.6502)**
	ARIMA						−0.4808
							(0.3167)

The bold number in brackets are *p*-values.

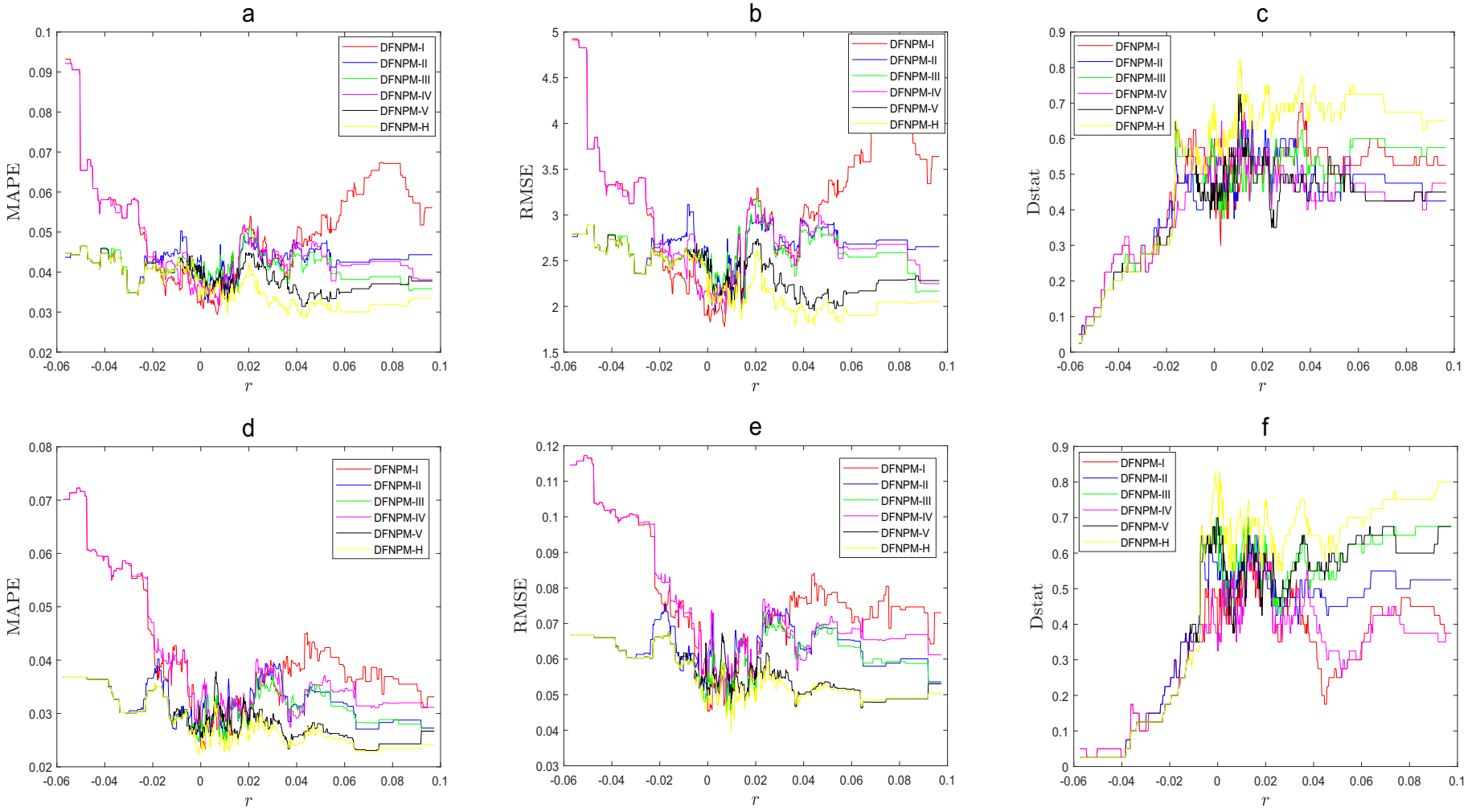

Fig. 8. Evolution of prediction accuracy with threshold values change (a) evolution of MAPE of crude oil price prediction (b) evolution of RMSE of crude oil price prediction (c) evolution of Dstat of crude oil price prediction (d) evolution of MAPE of gasoline price prediction (e) evolution of RMSE of gasoline price prediction (f) evolution of Dstat of gasoline price prediction.

network have relatively good effects in projecting tendencies in data fluctuations.

3.3. Comparison between DFNPMs and traditional prediction models

On the basis of sample data in part 3.2, we select four commonly used traditional prediction models: grey prediction model (GM), exponential smoothing model (ESM), autoregressive integrated moving average model (ARIMA) and radial basis function neural network model (RBF), and then compare their prediction effects with those of DFNPM-III, DFNPM-V and DFNPM-H. The comparison results of these seven models are shown in Fig. 7(a, b).

When we use the seven prediction models to predict the price of crude oil, as shown in Fig. 7(a), in terms of the accuracy of indicator MAPE, the ranking of these models is: DFNPM-H > DFNPM-V > DFNPM-III > ARIMA > RBF > GM > ESM; in terms of indicator RMSE, the ranking of the seven models is: DFNPM-H > DFNPM-V > DFNPM-III > ARIMA > RBF > GM > ESM; and in terms of indicator Dstat, the seven models are ranked as follows: DFNPM-H > DFNPM-III > DFNPM-V > RBF > GM > ARIMA > ESM. When we use the seven prediction models to predict gasoline price, as shown in Fig. 7(b), in terms of the accuracy of indicator MAPE, the ranking of these models is: DFNPM-H > DFNPM-V > DFNPM-III > ARIMA > RBF > ESM > GM; in terms of index RMSE, the ranking of the seven models is: DFNPM-H > DFNPM-V > DFNPM-III > ARIMA > RBF > GM > ESM; and in terms of indicator Dstat, the seven models are ranked as follows: DFNPM-H > DFNPM-III = DFNPM-V > GM = ARIMA = RBF > ESM. We can see that compared to traditional prediction models GM, ESM, ARIMA and BFR, DFNPMs are more accurate, in particular in predicting tendencies in oil price fluctuations.

In using the DM test to statistically confirm our conclusions, we use the *DMS* value of Eq. (3.4) and the *p*-value to measure how much the test model is an improvement over the benchmark model. Table 2 lists the corresponding *DMS* values and *p*-values (in brackets). Note that the *p*-values of the DFNPM-V and DFNPM-H forecasting models are over 10% smaller than those of the four traditional prediction models in both cases of crude oil price and gasoline price data. This indicates that the DFNPM-V and DFNPM-H models are statistically more effective than the four traditional prediction models. Note that because the *p*-values are above 10% neither the three DFNPM models (i.e., DFNPM-III, DFNPM-V and DFNPM-H) nor the four traditional prediction models (i.e., GM, ESM, ARIMA and RBF) are unmistakably superior.

3.4. The impact of changes in threshold values on prediction accuracy

Through the analysis in Step 1, we know that choosing a different threshold value affects the structure of data fluctuation network, which in turn influences the collection of effective information, thereby influencing the prediction accuracy of the models. As we can see in Fig. 5, under the same preliminary threshold value, when we select 2000 data items as the sample, predictions about crude oil and gasoline prices will be generally less accurate than predictions made with a sample size of 7500. In this part, we will explore, on the premise of the same sample size, the impacts of different preliminary threshold values on the prediction accuracy of the models. After selecting 2000 data items as the sample, we use Eq. (2.1) and determine that the preliminary threshold values r_0 of crude oil and gasoline are 0.0161 and 0.0165. Allowing the values range from −0.05 to 0.1, we get Fig. 8(a, b, c) showing how the accuracy of the six models predicting crude oil price varies with the threshold, and Fig. 8(d, e, f) displaying how the accuracy of the six models predicting gasoline price varies with the threshold.

As we can see in Fig. 8, as threshold values change, both MAPE and RMSE of models predicting crude oil and gasoline prices moves downward, then goes upward and finally turns stable, this suggests that there is a certain threshold value that brings a minimum level of MAPE and RMSE. The direction accuracy indicator Dstat first moves upward, then goes downward and finally turns stable, which indicates that there is a certain threshold value that brings a maximum level the indicator. Furthermore, according to calculations in Fig. 8, we can draw Fig. 9 (a, b) demonstrating the prediction accuracy of crude oil and gasoline prices at preliminary threshold value and at optimal threshold value. As shown in Fig. 9(a), when we use six DFNPMs to predict crude oil price, at preliminary threshold value, their loss function MAPE decreases by 10.20%–26.81%, with an average decrease of 15.87%; their loss function RMSE drops by 7.40%–30.31%, with an average decrease of 22.10%; and their prediction indicator Dstat rises by 0–40%, with an average increase of 18.96%. As shown in Fig. 9(b), when we use six DFNPMs to predict gasoline price, at preliminary threshold value, their loss function MAPE decreases by 13.61%–27.73%, with an average decrease of 17.67%; their loss function RMSE drops by 8.50%–30.73%, with an average decrease of 22.97%; and their prediction indicator Dstat rises by 4%–33%, with an average increase of 19.36%. The results of above empirical analysis prove that adjusting threshold value to the optimal point can improve the prediction accuracy of models. In effect, the analysis also provides us a method to choose an optimal threshold value when we use DFNPMs to make predictions. That is, calculate a preliminary threshold value with Eq. (2.1) according to sample data, choose a series of threshold values next to preliminary value, build DFNPMs corresponding to each threshold value, test the accuracy of prediction results for each model, and on the basis of test results, use Eq. (2.3) to determine the optimal threshold value.

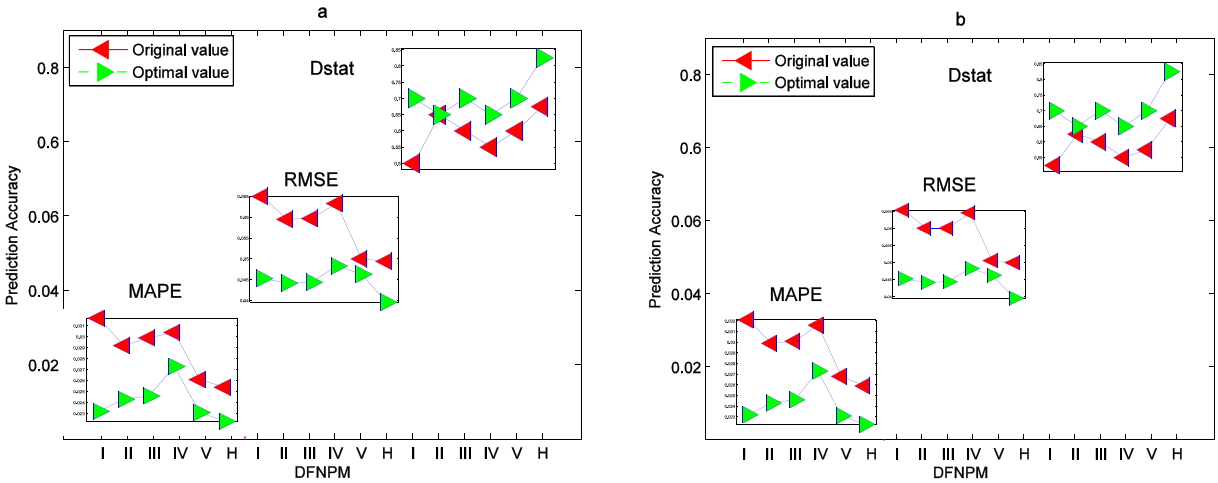

Fig. 9. A comparison of the prediction accuracy of original threshold and optimal threshold (a) crude oil price prediction (b) gasoline price prediction.

4. Discussions

This paper proposes a new time series prediction method based on data fluctuation network, named data fluctuation networks predictive model (DFNPM). The basic idea of the method is: convert a time series into a data fluctuation network, use the topological structure of the data fluctuation network to collect the fluctuation features of time series and make predictions about the time series with collected effective features. Compared with traditional prediction models, DFNPMs offer a new method for collecting the fluctuations features of time series. The results of the numerical simulation also show that a larger sample size leads to higher prediction accuracy of DFNPMs. Therefore, these models can effectively make predictions by using the effective information of the history data of times series, and accurately predict the fluctuation trends of times series by using the information about the topological structure of complicated data network. In addition to relatively high prediction accuracy, DFNPMs can also disclose the features of time series fluctuations, a function that is lacked in traditional prediction models. In dealing with data with relatively small sample size, adjusting the threshold value is feasible to improve the prediction accuracy of DFNPMs.

In the modeling part, we have proposed five prediction node rules by using the topological structure of complicated data network. In fact, there are many other topological indicators for describing the features of the topological structure of data network, such as clustering coefficient and intermediate number. Further research is needed to explore how to make use of these topological indicators to build prediction models. The results of numerical simulation show that prediction models with compound rules are more accurate in predicting prices and tendencies in price fluctuations. This paper only discusses the model composited by DFNPM-III and DFNPM-V, while it remains to be explored how to build prediction models composited by other single models to improve prediction accuracy. In recent years, along with the rapid development of network science, link prediction in networks has been widely put into application (Lü and Zhou, 2011). The question of how to combine link prediction and DFNPM to build prediction models with higher accuracy is worthy of in-depth research.

Acknowledgements

The Research was supported by the following foundations: The National Natural Science Foundation of China (71503132), the Major Project of the National Natural Science Foundation of China (71690242, 91546118), Qing Lan Project of Jiangsu Province (SJ201715), University Natural Science Foundation of Jiangsu Province (14KJA110001), Jiangsu Center for Collaborative Innovation in Geographical Information Resource Development and Application.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eneco.2018.02.021.

References

An, H.Z., Gao, X.Y., Fang, W., Huang, X., Ding, Y.H., 2014. The role of fluctuating modes of autocorrelation in crude oil prices. Physica A 393, 382–390.
Boser, B.E., Guyon, I.M., Vapnik, V.N., 1992. A training algorithm for optimal margin classifiers. Proceedings of the Fifth Annual Workshop on Computational Learning Theory. ACM, pp. 144–152.
Box, G.E.P., Pierce, D.A., 1970. Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. J. Am. Stat. Assoc. 65 (332), 1509–1526.
Chen, W.D., Xu, H., Guo, Q., 2010. Dynamic analysis on the topological properties of the complex network of international oil prices. Acta Phys. Sin. (7), 4514–4523.
Chiroma, H., Abdulkareem, S., Herawan, T., 2015. Evolutionary neural network model for West Texas intermediate crude oil price prediction. Appl. Energy 142, 266–273.
De Gooijer, J.G., Kumar, K., 1992. Some recent developments in non-linear time series modelling, testing, and forecasting. Int. J. Forecast. 8 (2), 135–156.
Dijk, D., Teräsvirta, T., Franses, P.H., 2002. Smooth transition autoregressive models—a survey of recent developments. Econ. Rev. 21 (1), 1–47.
Kac, M., 1947. Random walk and the theory of Brownian motion. Am. Math. Mon. 54 (7), 369–391.
Khashman, A., Nwulu, N., 2011. Intelligent prediction of crude oil price using support vector machines. Applied Machine Intelligence and Informatics (SAMI), 2011 Ninth International Symposium on IEEE, pp. 165–169 (January).
Lacasa, L., Luque, B., Ballesteros, F., et al., 2008. From time series to complex networks: the visibility graph. Proc. Natl. Acad. Sci. 105 (13), 4972–4975.
Lanza, A., Manera, M., Giovannini, M., 2005. Modeling and forecasting cointegrated relationships among heavy oil and product prices. Energy Econ. 27 (6), 831–848.
Li, S., Ge, Y., 2013. Crude oil price prediction based on a dynamic correcting support vector regression machine. Abstr. Appl. Anal. 1–7.
Li, X.X., Yu, L., Tang, L., Dai, W., 2013. Coupling firefly algorithm and least squares support vector regression for crude oil price forecasting. Business Intelligence and Financial Engineering (BIFE), 2013 Sixth International Conference on. IEEE, pp. 80–83 (November).
Liu, H., Tian, H.Q., Pan, D.F., Li, Y.F., 2013. Forecasting models for wind speed using wavelet, wavelet packet, time series and artificial neural networks. Appl. Energy 107, 191–208.
Lü, L., Zhou, T., 2011. Link prediction in complex networks: a survey[J]. Physica A Stat. Mech. Appl. 390 (6), 1150–1170.
Makridakis, S., 1993. Accuracy measures: theoretical and practical concerns. Int. J. Forecast. 9 (4), 527–529.
Mika, S., Ratsch, G., Weston, J., et al., 1999. Fisher discriminant analysis with kernels[C]// neural networks for signal processing IX, 1999. Proceedings of the 1999 IEEE Signal Processing Society Workshop. IEEE, pp. 41–48.
Mirmirani, S., Li, H.C., 2005. A comparison of VAR and neural networks with genetic algorithm in forecasting price of oil. Adv. Econ. 19, 203–223.
Moody, J., Darken, C.J., 1989. Fast learning in networks of locally-tuned processing units. Neural Comput. 1 (2), 281–294.
Morana, C., 2001. A semiparametric approach to short-term oil price forecasting. Energy Econ. 23 (3), 325–338.
Movagharnejad, K., Mehdizadeh, B., Banihashemi, M., Masoud, S.K., 2011. Forecasting the differences between various commercial oil prices in the Persian Gulf region by neural network. Energy 36 (7), 3979–3984.
Murat, A., Tokat, E., 2009. Forecasting oil price movements with crack spread futures. Energy Econ. 31 (1), 85–90.
Niu, D., Wang, Y., Wu, D.D., 2010. Power load forecasting using support vector machine and ant colony optimization. Expert Syst. Appl. 37 (3), 2531–2539.
Nomikos, N., Andriosopoulos, K., 2012. Modelling energy spot prices: empirical evidence from NYMEX. Energy Econ. 34 (4), 1153–1169.
Tang, L., Yu, L., Wang, S., Li, J.P., Wang, S.Y., 2012. A novel hybrid ensemble learning paradigm for nuclear energy consumption forecasting. Appl. Energy 93, 432–443.
Tay, F.E.H., Cao, L.J., 2002. Modified support vector machines in financial time series forecasting[J]. Neurocomputing 48 (1), 847–861.
Wang, Y.H., 2009. Nonlinear neural network forecasting model for stock index option price: hybrid GJR–GARCH approach. Expert Syst. Appl. 36 (1), 564–570.
Wang, M., Tian, L., 2016. From time series to complex networks: the phase space coarse graining[J]. Physica A Stat. Mech. Appl. 461, 456–468.
Wang, S.Y., Yu, L., Lai, K.K., 2005. Crude oil price forecasting with TEI@I methodology. J. Syst. Sci. Complex. 18 (2), 145–166.
Wang, J.J., Wang, J.Z., Zhang, Z.G., et al., 2012. Stock index forecasting based on a hybrid model. Omega 40 (6), 758–766.
Wang, M., Chen, Y., Tian, L., et al., 2016a. Fluctuation behavior analysis of international crude oil and gasoline price based on complex network perspective. Appl. Energy 175, 109–127.
Wang, M., Tian, L., Du, R., 2016b. Research on the interaction patterns among the global crude oil import dependency countries: a complex network approach. Appl. Energy 180, 779–791.
Wang, M., Tian, L., Xu, H., et al., 2017. Systemic risk and spatiotemporal dynamics of the consumer market of China. Physica A Stat. Mech. Appl. 473, 188–204.
Winkler, R.L., 1989. Combining forecasts: a philosophical basis and some current issues. Int. J. Forecast. 5 (4), 605–609.
Xiang, Y., Zhuang, X.H., 2013. Application of ARIMA model in short-term prediction of international crude oil price. Adv. Mater. Res. 798, 979–982.
Xie, W., Yu, L., Xu, S., Wang, S.Y., 2006. A new method for crude oil price forecasting based on support vector machines. Computational Science–ICCS 2006. Springer, Berlin Heidelberg, pp. 444–451.
Xu, X., Zhang, J., Small, M., 2008. Superfamily phenomena and motifs of networks induced from time series. Proc. Natl. Acad. Sci. 105 (50), 19601–19605.
Yu, L., Wang, S.Y., Lai, K.K., 2008. Forecasting crude oil price with an EMD-based neural network ensemble learning paradigm. Energy Econ. 30 (5), 2623–2635.
Yu, L., Zhao, Y., Tang, L., 2014. A compressed sensing based AI learning paradigm for crude oil price forecasting. Energy Econ. 46, 236–245.
Zhang, J., Small, M., 2006. Complex network from pseudoperiodic time series: topology versus dynamics. Phys. Rev. Lett. 96 (23), 238701.
Zhang, X., Lai, K.K., Wang, S.Y., 2008. A new approach for crude oil price analysis based on empirical mode decomposition. Energy Econ. 30 (3), 905–918.
Zhang, J.L., Zhang, Y.J., Zhang, L., 2015. A novel hybrid method for crude oil price forecasting. Energy Econ. 49, 649–659.