A Neural Network-based Ensemble Prediction using PMRS and ECM

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> > Abstract

Crude oil plays a significant role in the modern society and its price prediction attracts more and more attentions, not only for its importance to the modern industry, but also for its complex price movement. Based on PMRS, ECM and NN, this paper presents an integrated model to forecast crude oil prices. In the proposed model, PMRS is first used to model the trend of crude oil price, and then ECM is offered to establish to forecasting errors. Finally, NN is employed to integrate the results from the ones of PMRS and ECM to make the final forecasting values more accurate and desirable. The WTI spot prices and a set of financial indicators are utilized as inputs for the validation purpose. The empirical results show that the proposed integrated model can significantly improve the forecasting performance, compared with other four forecasting models, and it can be an alternative tool to predict crude oil prices.

1. Introduction

Crude oil is well known for its wide price volatility and has significant effects on global economic activities. For the crude oil-importing countries, high oil prices often lead to an increase in inflation and subsequently hurt of economies; and for the crude oil-exporting country, low oil prices may result in economic recession and political instability [1]. Besides the price levels, economic losses are also driven by swings of crude oil prices. Since crude oil price is one of the critical important resources in countries, it has been paid much attention by governments, enterprises and investors. Although crude oil prices, influenced by many complicated

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factors, appear highly nonlinear and even chaotic [2-4], a number of crude oil price forecast models have been proposed to assist practitioners and investors for decision support.

For the important of crude oil prediction, there have been a lot of studies on crude oil price prediction including qualitative and quantitative methods. Among the qualitative methods, for example, Nelson et al. [5] suggested the Delphi method to predict oil prices for the California Energy Commission.

The quantitative methods can be divided into two types: theory-based models and data-driven models. Theory-based models use economic theories, such as exhaustible resources [6], and supply-demand equilibrium schedule to analyze world crude oil market and crude oil price volatility [7], while data-driven methods develop models and approaches, such as time series methods [8-11], econometric models [12-15] and data mining tools [16-20] to predict crude oil price directly.

There are abundant studies on crude oil prices prediction using time series and econometric methods. Hou and Suardi [8] proposed a nonparametric GARCH model to analyze crude oil price return volatility, and Kang et al. [9] offered CGARCH and FIGARCH to predict crude oil volatility. Wei et al. [10] suggested using GARCH-class methods to model the crude oil market volatility, while Cheong [11] developed ARCH-type models. , Abramson and Finizza [12] used belief networks to prediction crude oil prices. Lanza et al. [13] investigated crude oil prices through error correction models (ECM), and Ye et al. [14] considered crude oil inventory to improve the forecast performance. Furthermore, Sadorsky [15] compared several different univariate and multivariate models such as TGARCH and GARCH to estimate the volatility in petroleum futures price returns.

However, the traditional time series and econometric models are built on linear assumptions and they cannot capture the nonlinear patterns hidden in the crude oil price series. With the development of data mining (DM) and artificial intelligence (AI), DM/AI methods have been designed to analyze and forecast crude oil price efficiently and effectively [16-20]. For example, Aminian and Shahhosseini [16] proposed an ANN model to predict crude oil behavior. Similarly, Kashani [17] employed optimized ANN to forecast crude oil prices, while Olatunji et al. [18] suggested a type-2 fuzzy logic system. Yu et al. [19] suggested an EMD-based neural network model to predict crude oil prices. Furthermore, Pang et al. [20] modeled the relationship between crude oil prices and inventory using WNN to predict crude oil prices.

Pattern modeling and recognition system (PMRS), a local approximation approach tool proposed by Singh and Fieldsend [21], have been used for the financial time series forecasting. Recently, several studies have been done to show the advantages of PMRS in time series prediction [22-25], especially in crude oil prediction [26].

However, the forecasted results are not accurate enough because of the complexity of the oil price movement [27]. The main reason for this is that the rules of the data change are not always the same. For example, oil prices had risen three dollars in one month but the following ones took two months to have the same price change. These phenomena may result from the differences of the time and market conditions, although the rules behind it may be similar [28]. Hence the historical rules may have some similarities other than to be the same. Based on these concerns, we build a model to identify the differences of the time and market conditions based on the econometrics. The error correction model is chosen for its excellent feature of capturing the tendency of the difference [29].

What's more, since a simple integration, such as a simple linear integration, cannot identify the relationships among the actual oil prices, especially for the abnormal points, we include a nonlinear integration of the forecast results, generated by PMRS and ECM, based on neural network (NN) model.

The rest of the paper is organized as follows. Some basic concepts and algorithms are introduced in Section 2. In Section 3, the proposed model, which integrates an improved PMRS, a PCA based ECM model, and the NN model for final integration, are proposed. In Section 4, the performance of the proposed model is evaluated and compared with ones of some baseline models. Empirical analysis shows that the proposed model outperforms other baseline models. The conclusion and future work are summarized in Section 5.

2. Introduction to basic models

In this section, pattern modeling and recognition system (PMRS), an error correction model (ECM), and a neural network (NN) are introduced successively.

2.1. PMRS

PMRS, short from Pattern modeling and recognition system, is a local approximation tool for time series forecasting. It works as follows. Suppose an original time series y described as $\{y_1, y_2, \dots, y_n\}$. The current state s_c can be described as $\{y_{n-k+1}, y_{n-k+2}, \dots, y_n\}$ in the same way. There exists s_p , $\{y_{j-k+1}, y_{j-k+2}, \dots, y_j\}$ which is defined as the nearest neighbor of state sc and can be derived from time series data by pattern matching approaches, where k is the size of the state. The past state $\{y_{j+1}, y_{j+2}, \dots, y_{j+m}\}$ that follows the nearest neighbor of s_c can be utilized to forecast the future state that is defined as $\{y_{n+1}, y_{n+2}, \dots, y_{n+m}\}$, where m is its length. Furthermore, a segment in the data defined as a series v vector is $\delta = (\delta_i, \delta_{i+1}, \dots, \delta_{i+k-1})$, where k is the size of segment δ and $\delta_i = y_{i+1} - y_i, 1 \le i \le j \le i + k - k$ $1 \le n-1$.The difference between two states $\{y_p, y_{p+1}, \dots, y_{p+k}\}$ and $\{y_q, y_{q+1}, \dots, y_{q+k}\}$ can be described by $\nabla = \sum_{i=1}^{k} w_i (\delta_{p+i-1} - \delta_{q+i-1})$, where $1 \le p \le p + k \le n, 1 \le q \le q + n \le n$ and Wi stands for the weights. A pattern in the time series is defined as $\rho = \{b_i, b_{i+1}, \dots, b_{i+k-1}\}$, where b_j is a binary value. $b_i = 1$ when $y_{i+1} \ge y_i$; otherwise $b_i = 0$. Therefore, b_i is called tag. The nearest neighbor state of s_c will be derived from matching the pattern of the past state and the one of s_c in PMRS. In this way, the forecast based on the following pattern of the pattern for the nearest neighbor state can be given.

2.2. ECM

Error correction model (ECM) is a dynamical model with characteristics of feeding long-term dynamics into short-run ones. And these characteristics are about the deviation of the present state. ECMs are able to describe the impacts of an independent variable x on a dependent variable y. Through the coefficient of each independent variable, the extent at which the dependent variable will change

can be identified, if there is a unit change in independent variable.

In order to apply error correction in multi-factor model, vector correction model is employed here (VECM).

In VECM, the number of independent variables can be varied while there is only one dependent variable. The differences between adjacent time points of independent variants are used as the new independent variables for regression. The coefficients of independent variables can be determined by method of least squares. Thus, when the differences between present point and certain past points of independent variables are given, VECM is capable of forecasting the differences of dependent variables. And these forecasted differences in dependent variables can be helpful in forecasting the future crude oil prices. These differences can be combined with the oil prices forecasted to generate the new predicted prices. And because of the characteristics of feeding long-term dynamics into shot-run ones of VECM, the inclusion of differences of time series can reflect short-term variation, which makes the prediction more reasonable and convincing. As suggested in [30], the formula can be denoted as follow:

$$\Delta Y = \sum_{i=1}^{m} \beta_i \Delta x_i + \varepsilon \tag{1}$$

where ΔY denotes the difference of dependent variable, and Δx_i denote the difference of independent variables. β_i is the coefficient of Δx_i , and ε is error term.

2.3. Neural networks

Neural networks (NNs) are typical intelligent learning models that simulate the structure and the function of neural networks of humans' brains, widely used in some practical domains. It is consisted of a group of artificial neurons which are connected and mutually influenced. A weights adaptation approach is utilized to determine the weights of each neurons and finally neurons process information according to their weights [31].

The back-propagation neural network model (BPNN) is one of the commonly used neural network models. The typical structure of BPNN is shown in Figure 1.



Figure 1 The typical structure of BPNN

Within BPNN, the main point is that the errors at the output layer will be propagated backward to the input layer through a defined hidden layer, which is the middle part of the network structure.

3. The proposed method

In our proposed method, PMRS is first used to predict crude oil based on the original crude oil price data, and then ECM is employed to model the error generated by PMRS. Finally, the outputs by PMRS and ECM are integrated by BPNN, to get the final results. The proposed model is described in Figure 2.

As can be seen from Figure 2, the dataset including crude oil time series and economic indicator time series can be used as inputs into our proposed model. y' denotes the forecast directly comes out of an improved PMRS. Y_V is a vector of the true values of the valid set when using the best size of matching pattern. Y'_{V} is a vector of forecasted values of the valid set when using the best size of matching pattern. ΔY is a vector of the differences between Y_V and Y'_V (i.e., $\Delta Y' = Y_V - Y'_V$). $\Delta Y'$ is a vector of the forecasted differences between the actual values of the valid set and the forecasts, directly generated by PMRS, based on the valid set. $\Delta Y'$ is generated by the econometric model based on the co-integration theory. $\Delta y^{"}$, derived from the co-integration theory and econometric model, represents the forecasted differences between the actual oil prices and y'. Finally, y^{T} stands for the final forecast generated by BPNN.



Figure 2 The framework for crude oil price prediction

3.1. The improved PMRS

Improved PMRS is different from basic PMRS by the including of stochastic time effective function which is introduced by Liao and Wang [22], and the modification of size and offset. It is used to produce vector y' and $\Delta Y'$ aforementioned. The details of the improved PMRS algorithm can be implemented in the four steps as follows:

Step 1: Choose a pattern. When the PMRS is used for crude oil prediction, we may choose a pattern current time series $p' = (y_{n-k}, \dots, y_{n-2}, y_{n-1})$.

Step 2: Find the matching. The closest historical matching of current time series $p' = (y_{n-k}, \cdots, y_{n-2}, y_{n-1})$ can be discovered by minimizing offset. it's obvious that the nearer the time of the historical data is to the present, the stronger impact the data have on the present data for the time serried data, such as the global stock index. Actually a stochastic time effective function can be used to judge the true value of the data in the history which is defined as follows [22]:

$$E(t_1 - t_n) = \frac{1}{\tau} \exp\{\int_{t_1}^{t_n} \mu(t) dt + \int_{t_1}^{t_n} \sigma(t) dB(t)\}$$
(2)

where τ (>0) stand for the time strength coefficient, t_1 represents the newest data's time or the current

time in the series, and t_n is antarget time point in the series. $\mu(t)$ stands for the drift function (or the trend term) and the volatility function is defined as $\sigma(t)$. The standard Brownian motion is defined as B(t). So the stochastic time function is taken into consideration to find the nearest neighbor for the current pattern in the history data and make an adjustment for the value following the most similar past pattern to get the forecast. As stated in subsection 2.1, the offset is defined as $\nabla = \sum_{i=1}^{k} w_i (\delta_{n-i} - \delta_{j-i})$ in the original PMRS. We redefine the offset as $\nabla = \sum_{i=1}^{k} w_i (\delta_{n-i} - \delta_{j-i})^2$ in the improved PMRS because the square can describe the difference between two patterns more reasonable.

Step 3: Calculate the errors. Though the formula $y_{n+1} = y_n \pm \left[w\beta_1 + (1-w)\beta_2 \right]^* \delta_j , \quad \text{where}$ $\delta_j = \frac{1}{k} \left[\sum_{i=1}^k \frac{\delta_{n-i}}{\delta_{j-1}} * e^{\frac{1}{t-1}} \right] , \quad \text{and} \quad \beta_1 \quad \text{and} \quad \beta_2 \quad \text{are}$

parameters, which represent the differences between the current price fluctuation and the similar historical one, the error can be calculated by commonly used evaluation criteria.

Step 4: Determine the parameters. Before confirming the parameters, the dataset used to determine the parameters can divided into three parts including training set, testing set and validation set. The proportion of training set and testing set should be fixed when we want to get forecast results directly by the improved PMRS. For example, the size of training set is 200 and the size of the testing set is 30. The validation set is used to evaluation the performance of our proposed method using different parameters. The structure of crude oil price dataset is shown in Figure 3.



After different parameters are used in modeling, the improved PRMS with smallest pattern size k and optimal parameters are obtained. So, the optimal IPRMS can be used to predict crude oil price trend.

As discussed above, the process of the improved PMRS can be described in Figure 4.



Figure 4 The process of the improved PMRS

3.2. Factor analysis using PCA

There are many factors which are able to influence the price of oil. And many related factors have some inside correlation between themselves. If we directly use these factors in our regression, the regression will suffer from the multicollinearity which will bring a lot of troubles to our estimation of regression parameter. In order to make our model reliable, we need to acquire necessary information use as much as possible. But as we have discussed before, if we take a lot of factors in our regression, we will have to face the problem of multicollinearity. Thus, we use principal component analysis (PCA) to fulfill the requirement of information and solve the problem of multicollinearity.

In PCA, we first choose many factors which may have some relation to the price of oil. These factors are chose according to the Pearson correlation coefficient. Then we use Bartlett Test of Sphericity, Kaiser-Meyer-Olkin test to find out the factors which have strong correlation between themselves. Taking advantage of component matrix, we can get the component score coefficient matrix. Finally, the number of factors is determined according to the eigenvalue.

In this paper, cumulative variance contribution rate is used to decide the number of eigenvalue. Cumulative variance contribution rate is defined as below:

$$a_{k} = \frac{\sum_{i=1}^{k} \lambda_{i}}{\sum_{i=1}^{p} \lambda_{i}}$$
(3)

The correlation matrix can be expressed as follow:

$$A = \begin{pmatrix} a_{11} & a_{21} & \cdots & a_{p1} \\ a_{12} & a_{22} & \cdots & a_{p2} \\ \vdots & \vdots & & \vdots \\ a_{1p} & a_{2p} & \cdots & a_{pp} \end{pmatrix}$$
(4)
$$= \begin{pmatrix} u_{11}\sqrt{\lambda_{1}} & u_{21}\sqrt{\lambda_{2}} & \cdots & u_{p1}\sqrt{\lambda_{p}} \\ u_{12}\sqrt{\lambda_{1}} & u_{22}\sqrt{\lambda_{2}} & \cdots & u_{p2}\sqrt{\lambda_{p}} \\ \vdots & & \vdots & & \vdots \\ u_{1p}\sqrt{\lambda_{1}} & u_{2p}\sqrt{\lambda_{1}} & \cdots & u_{pp}\sqrt{\lambda_{p}} \end{pmatrix}$$

where A is the correlation matrix.

According to reference [32], if cumulative variance contribution rate is bigger than 85%, the number of eigenvalue is k.

After we choose the eigenvalue according to cumulative variance contribution rate, we can get new component matrix as follows.

$$A = \begin{pmatrix} u_{11}\sqrt{\lambda_1} & u_{21}\sqrt{\lambda_2} & \cdots & u_{k1}\sqrt{\lambda_k} \\ u_{12}\sqrt{\lambda_1} & u_{22}\sqrt{\lambda_2} & \cdots & u_{k2}\sqrt{\lambda_k} \\ \vdots & \vdots & & \vdots \\ u_{1p}\sqrt{\lambda_1} & u_{2p}\sqrt{\lambda_1} & \cdots & u_{kp}\sqrt{\lambda_k} \end{pmatrix}$$
(5)

In this way, we can use much less factors and keep as much information as possible. And the fact that the new generated factors have much less correlation will enable us to avoid multicollinearity in regression. Since the new factors are generated from the original factors and they are the combination of the original factors, we need to give some meaning to these new factors. And these may easily be accomplished by looking at the coefficient in component score coefficient matrix. If the absolute value of the certain coefficient is great, then the new factors have much information of this original factor.

3.3. ECM modeling

As aforementioned, crude oil price movement is influenced by different factors in market environment, and the factors are often changed in different period. Thus, an ECM model is established using the economic indicators, refined by PCA.

$$\Delta Y' = \sum_{i=1}^{m} \beta_{i} \Delta \chi_{i} + \varepsilon$$
(6)

3.4. Neural network ensemble

As discussed above, when all the intermediate forecasting results including Y_V , Y'_V , ΔY , $\Delta Y'$, y' and $\Delta y''$ are obtained respectively, how to integrate these results for final result y^T is also a critically important issue.

The motivation behind using an integrated forecasting approach is to create a synergy effect that improves prediction power. Intuitively, a single integrated forecast can be derived from y', the forecast directly generated by PMRS, and $\Delta y^{"}$, the forecasted difference between the actual oil price and y' calculated by ECM:

$$y^T = y' + \Delta y^{"} \tag{7}$$

However, the kind of integration can't guarantee a better forecast under all circumstances. Thus these two parts (y' and Δy ["]) need to be integrated into a more accurate forecast. That is:

$$v^{T} = f(y', \Delta y") \tag{8}$$

The work left here is to determine a function f() that fits the relationship among the three parts. In our proposed model, BPNN is employed as the integration function.

4. Empirical analysis

In this section, several commonly used evaluation criteria are used to evaluate the performance of the proposed model and compare with those from other four baseline models.

4.1. Evaluation criteria

In order to identify the difference between the predicted value and actual oil price, we use Root Mean Square Error (*RMSE*) to quantify the difference which is calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - y_i)^2}{n}}$$
(9)

Furthermore, when we try to weigh the results of different models, we will use Mean Absolute Percentage Error (*MAPE*) as the criteria to judge the accuracy.

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{y_i - y'_i}{y_i} \right)$$
(10)

4.2. Empirical results

4.2.1. Data description

To validate the efficiency and effectiveness of the proposed model, WTI monthly spot price data from Jan. 1993 to Dec. 2012 is used for prediction purposes. The dataset first divided into three parts. The first part is the training set, in which the dada is from Jan. 1993 to Dec. 2004, and the second part is the testing set, in which the data is from Jan. 2005 to Dec. 2010. Accordingly, the data from Jan. 2011 to Dec. 2012 is offered as the validation set. Furthermore, some related economic indicators, such as world total oil gross imports, are also collected in the same period.

Through the improved PMRS, the estimated oil prices of each time point is generated, which are denoted as Y'_V . Similarly, the forecasted prices of the estimated time point can be generated, which are denoted as y'.The differences between actual values of prices in history and the estimated prices can be thus obtained and are denoted as ΔY .

According to PRMS, a period in the history which is used to predict the oil price can be found. Average values for each economic factor in this period then are calculated. Then we use the value of the economic factors at the point which is in 72 time points to minus the corresponding average value in the history. In that way, at each one in 72 time point records, value differences for each economic factor can be obtained. Differences in oil prices and the differences in economic factors are then used s to establish the vector error correction model (VECM). As soon as coefficients in the model are calculated, these models can be used to work out the literal differences in oil price for each of the 72 time point records. These literal differences are denoted as $\Delta Y'$.

Similarly, differences between the value of the estimated time point records and the actual average values in the history of economic factors can be obtained. Using these differences, literal differences between the estimated prices and the actual prices of oil can be calculated either, which is denoted as $\Delta y^{"}$. Based on the method of BPNN and the data of the forecasted differences in 72 time point records, our system can be adjusted to generate an optimal pattern to predict the oil prices under the given circumstance. After the optimal pattern in BPNN is worked out, we can take advantage of $\Delta y^{"}$ and y' to generate predicted price for the estimated time points, which is denoted as y^{T} .

It is noticeable that during the process of building ECM, PCA is employed to generate new factors. Since new factors keep as much information as possible while minimizing correlations among them, these transferred factors are helpful in establishing ECM. And these factors are also capable of reflecting characteristics of original factors, which can be observed from the coefficients in component matrix.

4.2.2. Experimental Results and Comparison

The validation of the proposed neural network based integrated model (NN-In) is carried out, and for comparison, other four baseline models, including the original PMRS (PMRS), the improved PMRS (IPMRS), BPNN, and a simple integration model (SI-In), are also used to forecast crude oil prices based on the same data. The experimental results can be shown in Figure 5.



Figure 5 The experimental results of five baseline models

According to RMSE and MAPE, the forecast performance of the five models is displayed in Table 1.

Table 1 The forecast performance of five forecasting

		III	54015		
	NN-In	SI-In	IPMRS	PMRS	NN
RMSE	6.519	8.411	8.007	12.093	15.007
MAPE	5.235	6.278	6.524	10.156	14.101

As can be seen from Figure 5 and Table 1, the improved PMRS can catch the tendency of the oil price more accurately when compared with the original PMRS. Meanwhile, although simple NN model cannot result a good forecast performance, it dose catch the change of the oil prices sometimes. Furthermore, it is obvious that the simple integration model and the proposed model do a better job than the other three models. When compared with the other three models, they can not only catch the tendency of the oil prices, but also narrow the gaps between the actual prices and predicted one. What's more, the proposed model can do a better job than the simple integration model, especially in controlling the abnormal forecast. As discussed above, it can be concluded that the proposed model performs better than the other benchmark models.

5. Conclusions

In this paper, a novel neural network based ensemble forecasting model is proposed based on PMRS, ECM and BPNN for the prediction of crude oil prices. In terms of evaluation criteria, the empirical results reveal that among the baseline models, the proposed integration models outperform other three individual models, and moreover, the neural network-based ensemble model is dominant. Meanwhile, the experimental results also indicate that our proposed method provides a new way for crude oil price prediction, and the proposed neural network-based ensemble forecasting method is a potential and feasible alternative to mine crude oil price trend.

In addition, this study also has some research questions for future studies. First, to further validate our proposed method, some additional experiments can be done from other data sources such as Brent oil prices. Second, how to integrate the final results more stably and accurately can be investigated in future. Third, when dealing with the crude oil prediction problem, social media and article news may also be considered to improve the prediction performance. Finally, the proposed model can also be applied to other research fields, especially to financial market.

6. Appendix

Table 2 shows the monthly spot oil prices for WTI, from Jan. 2011 to Dec. 2012, and the forecasting results of the proposed method and the other four baseline methods. Ac is short of the actual oil prices.

Month	Ac	NN-In	SI-In	IPMRS	PMRS	NN
201101	89.17	88.01	90.11	90.03	86.41	77.61
201102	88.58	86.22	84.83	90.30	88.37	94.21
201103	102.86	101.79	77.31	88.98	92.43	84.31
201104	109.53	101.93	102.72	107.39	95.81	87.44
201105	100.90	95.22	100.22	109.90	112.44	86.51
201106	96.26	98.89	101.97	102.60	114.52	90.36
201107	97.30	94.36	92.74	96.40	99.23	91.18
201108	86.33	98.40	97.78	102.37	107.55	114.50
201109	85.52	82.28	85.53	87.32	94.95	109.79
201110	86.32	82.19	85.97	85.58	95.67	96.29
201111	97.16	82.78	79.57	86.78	85.71	84.80
201112	98.56	98.36	102.51	104.79	82.72	101.09
201201	100.27	100.07	104.57	105.88	98.38	92.80
201202	102.20	96.47	98.78	101.40	88.47	79.17
201203	106.16	100.52	100.55	104.00	96.02	86.00
201204	103.32	103.64	101.98	106.71	91.87	115.85
201205	94.66	99.24	103.95	105.99	96.87	108.99
201206	82.30	96.83	97.12	100.05	115.04	105.94
201207	87.90	100.52	94.15	102.55	90.05	98.01
201208	94.13	87.44	88.831	89.96	85.69	107.30
201209	94.51	92.81	92.15	95.69	99.02	104.98
201210	89.49	88.47	88.51	96.61	93.04	96.26
201211	86.53	87.69	91.05	92.11	97.26	97.85
201212	87.86	83.37	84.64	86.77	87.45	91.52

Table 2 The crude oil prices and the forecasting results

Table 3 shows the 36 economic indicators chosen to set up the error correction model.

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I able	3	I he	36	economic	indicators

No	Name of the indicator
1	U.S. Ending Stocks excluding SPR of Crude Oil
2	Ending Stocks of Residual Fuel Oil
3	Ending Stocks of Distillate Fuel Oil
4	U.S. Ending Stocks excluding SPR of Crude Oil and Petroleum Products
5	U.S. Ending Stocks of Crude Oil and Petroleum Products
6	U.S. Ending Stocks of Kerosene-Type Jet Fuel

7	U.S. Ending Stocks of Propane and Propylene					
8	U.S. Crude Oil First Purchase Price					
9	U.S. less Alaskan North Slope Crude Oil First Purchase Price					
10	U.S. Crude Oil Stocks in Transit (on Ships) from Alaska					
11	Cushing, OK Crude Oil Future Contract 1					
12	Cushing, OK Crude Oil Future Contract 2					
13	Cushing, OK Crude Oil Future Contract 3					
14	Cushing, OK Crude Oil Future Contract 4					
15	U.S. Dollar Index					
16	Europe Brent Spot Price FOB					
17	Central Atlantic (PADD 1B) Ending Stocks of Distillate Fuel Oil					
18	Central Atlantic (PADD 1B) Ending Stocks of Total Gasoline					
19	U.S. Ending Stocks of Fuel Ethanol					
20	Lower Atalntic (PADD 1C) Ending Stocks of Total Gasoline					
21	New England (PADD 1A) Ending Stocks of Distillate Fuel Oil					
22	New England (PADD 1A) Ending Stocks of Total Gasoline					
23	U.S. Ending Stocks of Crude Oil in SPR					
24	OECD Total Consumption of Petroleum Products					
25	U.S. Total Consumption of Petroleum Products					
26	All commodities					
27	All imports excluding petroleum					
28	Foods, feeds, & beverages					
29	Agricultural foods, feeds & beverages, excluding distilled beverages					
30	U.S. Total Oil Net Imports					
31	OECD Total Oil Net Imports					
32	World Total Oil Net Imports					
33	U.S. Total Oil Gross Imports					
34	OECDTotal Oil Gross Imports					
35	World Total Oil Gross Imports					
36	U.S. Consumer Price Indexes (CPI)					

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